Product Preannouncements and Entry Deterrence in the U.S. Movie Industry

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Abstract

In many industries, firms preannounce their plans before making entry decisions or releasing new products. However, the literature shows little evidence that such public announcements are binding and have significant effects on competitive strategies of firms. In this paper, I analyze the role of product preannouncements in the context of the U.S. movie industry. Using a novel dataset of 60,000 release date announcements, I show that movie studios rarely change preannounced release dates of movies even when production delays of competitors vacate highly profitable release slots (e.g., Christmas weekend). This reluctance to change release dates suggests that studios face substantial switching costs. To study how these switching costs affect competitive outcomes, I develop and estimate a simple dynamic game of announcements. The estimation results reveal that major studios face higher switching costs than minor distributors and can credibly commit to release on high-demand dates by making public announcements. Overall, my analysis suggests that public announcements generate entry barriers by denying minor studios access to profitable release dates.

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1 Introduction

In many markets, firms preannounce their plans before making entry decisions or releasing new products. For example, auto manufacturers announce their new car models, video game developers preannounce new games, movie studios announce preliminary release dates of movies, and large retailers reveal their plans to open new stores in different locations. Empirical studies show that such announcements are widespread; in the United States and Germany over 50% of products are preannounced (Robertson, Eliashberg, and Rymon 1995; Bayus, Jain, and Rao 2001). According to prior research, firms make public announcements to share information about common demand and cost parameters with competitors (Doyle and Snyder 1999), coordinate on collusive strategies (Green and Porter 1984; Marshall and Marx 2008), or signal product quality (Schmalensee 1982). An additional reason for these announcements, however, is to deter competitors from entering the same geographical markets, developing similar products, or releasing products at the same time (Farrell and Saloner 1986; Gerlach 2004; Caruana and Einav 2008b). This deterrence strategy can be effective as long as the firm would incur prohibitive costs if it deviated from its preannounced action. However, the literature shows little evidence that such announcements are binding; nor does it explain which market features lend credibility to these announcements.

In this paper, I analyze the role public announcements play in the U.S. movie industry. This industry is an (almost) ideal setting for studying pre-market actions of firms because movie distributors routinely preannounce release dates of movies, all of which are documented in an industry magazine. To take advantage of this unique industry feature, I collect and analyze a dataset of around 60,000 release date announcements for 4,500 movies. When distributors announce release dates, they book screens in movie theaters and contract with promotion agents. Because these contracts are normally tied to a specific release date of a movie, distributors cannot freely change release dates without engaging in costly negotiations to do so. Additionally, since consumers learn release dates from trailers, they may perceive changes in release schedule as a signal that the movie is of poor quality, thus dissuading distributors from changing release dates for fear of losing consumers.[1] The main goal of this paper is to determine whether the costs of changing release dates, generated by binding contracts and consumer reputation, are sufficiently high to lend credibility to release date announcements.

Inferring the cost of switching release dates from announcements is difficult. Although these costs could be inferred from the general tendency of distributors to change release dates, their reluctance to switch dates can be explained by both switching costs and the unobserved profitability

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[1] Prior literature suggests that reneging on preannouncements can make a company lose reputation, making its future preannouncements less credible and dissuading consumers from buying its product (Eliashberg and Robertson 1988; Su and Rao 2010).
of different release dates. To solve this identification problem, I construct a novel dataset on major production delays experienced by different movies. Specifically, I collect this data by scraping news articles in newspapers and industry magazines and detecting all instances, in which a movie was delayed by the reasons unrelated to competition (e.g. injury of the leading actor). Such production delays force movies to change their release dates, thus vacating release slots. When the vacated slot is highly profitable, we can expect competing movies to respond by switching to the now open slot; distributor’s decision not to switch would then suggest the presence of non-trivial switching costs. Following this identification strategy, I study how movies respond to unexpected delays of competitors and show that studios indeed respond by switching to vacated time slots. In fact, the response is stronger after delays that occur five to eight months in advance, whereas movies rarely switch after delays occurring less than four months in advance. This fading response suggests that distributors become increasingly committed over time: they can freely switch release dates at the early stages of planning but have to incur substantial switching costs to make last-minute changes.

To study how the presence of switching costs affects final choices of release dates, I develop and estimate a simple dynamic model of announcements. In the model, each studio has multiple opportunities to announce and revise their movie release dates, but has to pay a switching cost for each revision. Revising release dates becomes increasingly costly as studios approach the last period of the game, reflecting the fact that making last-minute changes is difficult. The structure of this model is similar to the model of endogenous commitments in Caruana and Einav (2008b). Compared to their complete information model, however, in my model studios face uncertainty about the profitability of different release weeks; this uncertainty presents studios with a trade-off between committing to certain release dates and remaining flexible until they the uncertainty is resolved. I estimate the model by assuming that announcements and final release dates observed in the data are equilibrium outcomes of this dynamic game. The payoffs from releasing movies on different dates are specified using an estimated demand from Einav (2007). The goal of estimation is to quantify switching costs and use a series of counterfactuals to study how the ability of studios to make public announcements affects the final configuration of release dates.

The estimation results suggest that studios face substantial switching costs, confirming that announcements can serve as a tool of partial commitment. The magnitude of switching costs increases as studios approach final periods of the game, consistent with the reduced-form evidence from the data on production delays. In addition, I find that major distributors have higher switching costs than minor distributors. Using several counterfactual exercises, I demonstrate that this asymmetry in costs exacerbates market power of major studios: these studios use public announcements as a way to precommit and capture the most profitable release dates, leaving relatively unattractive dates to minor distributors. Consequently, setting switching costs to zero in the estimated model
decreases market concentration and increases the market share of minor distributors. Overall, these results illustrate how the presence of binding announcements can generate entry barriers by denying minor distributors access to profitable release dates.

Related Literature. This paper relates to theoretical work on commitment. There exists a burgeoning literature studying how the ability of players to make an initial binding action affects the outcomes of the game. Among recent attempts to revisit this topic, Quint and Einav (2005) and Caruana and Einav (2008b) develop a theoretical framework, in which identities of players who precommit in equilibrium are determined endogenously from the fundamentals of the model, e.g., based on the asymmetries in players’ payoffs. However, literature shows little evidence that such commitment behavior arises in real-world applications. Most of the empirical evidence we have is from laboratory experiments (Huck, Müller, and Normann, 2002; Fonseca, Huck, and Normann, 2005; Santos-Pinto, 2008). To the best of my knowledge, Caruana and Einav (2008a) is the only paper that studies commitment behavior of firms using data from a real-world market, showing that U.S. car manufacturers exaggerate their preannounced production targets in order to gain a Stackelberg leadership position. I contribute to this literature by providing empirical evidence that U.S. movie studios use release date announcements as a way of committing to release their movies in the most profitable time slots. The evidence I present here also validates some assumptions commonly made in theoretical literature, including the assumption that players differ in their ability to make commitments.

The second related literature is on the estimation of entry games. Structural entry models are often used to analyze competition in time. Goettler and Shachar (2001) develop a dynamic game capturing strategic scheduling decisions of television networks, although they do not explicitly use the model for estimation. In a different setting, Sweeting (2009) estimates a structural model in which radio stations strategically choose the timing of advertising. The closest to my analysis, however, is the paper of Einav (2010) who develops a dynamic model of release timing in the movie industry. Using the estimated model, he demonstrates that distributors trade-off between releasing their movies during the peak-demand periods and facing milder competition from other films. Compared to his modeling framework, a novel feature of my model is that distributors have several chances to announce and revise the release dates of their movies, a feature that makes it possible to analyze how preannouncements affect the final release schedule. In addition, I estimate a release timing game with a different purpose: Einav (2010) uses his estimates to analyze the

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2 Some papers from this literature are Hamilton and Slutsky (1990), Van Damme and Hurkens (1999), Maggi (1996), and Henkel (2002).

3 Along the same lines, Calcagno, Kamada, Lovo, and Sugaya (2014) solve for equilibria in a model where players choose and repeatedly revise the actions, which are then implemented at a predetermined deadline.
trade-off between profitability and competition, whereas I focus on studying how the presence of binding announcements affects the final release timing decisions, changes market concentration, and generates entry barriers for minor distributors.

The rest of the paper is organized as follows. Section 2 describes institutional details of the U.S. movie industry and presents the data. Section 3 develops a simple model of competition and derives testable predictions, while Section 4 presents reduced-form evidence consistent with these predictions. In Section 5, I expand the simple model to a more general setting and discuss estimation, while related estimation results and counterfactual experiments. Section 7 concludes by discussing the relevance of results to other settings.

2 Institutional Details and Data

2.1 The U.S. Movie Industry

The U.S. movie industry consists of three main players: producers, who make the movies; distributors, who are responsible for domestic and international distribution; and exhibitors, who own movie theaters. This paper concentrates on distributors and studies how they choose release dates for their movies.

2.1.1 Release date decisions

Among the important decisions distributors must make, the choice of a release date is probably the most important one. A release date plays a crucial role because the average movie earns over 40% of its domestic revenues during the opening week. High revenues at this time generate positive word-of-mouth, giving distributors an opportunity to advertise the film as “America’s most popular movie” in the following weeks. In addition, the successful opening of a movie may increase revenues from other markets including the DVD market, video on demand market, and pay television. With prices playing almost no role in this market, choosing release dates is thus the most important competition tool available to distributors.

4The description of institutional details in this section is mainly based on my conversations with industry experts as well as on the paper of Einav (2007) and the books of Marich (2005) and Moul (2005).

5This figure is based on the revenue data for movies released in the U.S. domestic market between 1983 and 2014. See Section 2.2. for detailed description of the data.

6Moretti (2011) provides detailed discussion of the word-of-mouth effect in the movie industry.

7Marich (2005) discusses that revenues studios earn from licensing films to television channels are closely related to box-office revenues collected domestically by a given film.

8In the U.S. movie theaters, ticket prices rarely differ across movies and over time. Orbach and Einav (2007) document this uniform pricing puzzle and discuss potential explanations.
When choosing release dates, distributors trade off between releasing a movie during a high-demand week or facing softer competition from the movies of other studios (Einav 2007). On one hand, since some time periods such as Thanksgiving and Christmas are more popular among moviegoers, distributors try to release their movies during these peak-demand periods. On the other hand, competition is typically more intense during these weeks, forcing their movies to compete with high-budget films from other studios. Therefore, although distributors prefer to release movies during weeks of high demand, they must also attempt to deter competitors from choosing the same release dates.

2.1.2 Pre-release announcements

A key feature of the industry is that distributors preannounce release dates of their movies. Because information about these announcements is routinely disseminated in advertising, newspapers, and industry magazines, the preannounced release dates of movies are typically observed both by competing distributors and theater owners. Once the announcement is made, a studio can in principle revise it as many times as possible, notifying industry participants of the corresponding changes in the release schedule. However, when studios make their first announcements, they typically start preparing for the opening of a movie by making irreversible investments. These investments may in turn generate switching costs, thereby preventing a studio from switching release dates at later stages.

Switching costs may arise from three different sources: renegotiation costs, reaction of consumers to release date changes, and reputational costs. First, to prepare for the release, a studio needs to contract with theaters to ensure that a movie will be exhibited on a sufficient number of screens, and with promotion agents, who coordinate advertising, organize tie-in promotions with fast-food restaurants, and license merchandise to retail stores. Since these contracts are normally associated with a specific release date of a movie, once a studio has committed to these arrangements, changing the release date becomes costly as it forces studios to renegotiate contracts. Changing contract terms with movie theaters is costly because available screens and show times get booked relatively fast, making it difficult for theater owners to shift a movie’s release to another week. This is especially true for last-minute changes, as in few months before release, theater schedules are already full and difficult to change. Similarly, promotional events are also costly to change because pre-booked advertising slots need to be shifted to other weeks.

The second potential source of switching costs is that consumers can react negatively to release date changes. When preparing for the release, movie studios make release dates of their movies observable to consumers by advertising them in trailers, on official posters, and on billboards.\(^9\)

\(^9\)To illustrate this observation empirically, I collected data on movie trailers released in U.S in 2010-2016. Specifi-
Consumers may perceive changes in the release schedule as a signal that production issues may negatively impact the quality of a movie, making distributors reluctant to change release dates out of fear of losing consumers. This mechanism is consistent with the previous literature, which emphasizes that reneging on preannouncements can make a company lose reputation, dissuading consumers from buying its product (Eliashberg and Robertson 1988; Su and Rao, 2010).

Finally, studios may be reluctant to switch release dates because of potential damage to their reputation. The U.S. movie industry is characterized by a relatively stable set of distributors repeatedly competing with each other season after season. In this repeated game, studios can theoretically build their reputation and use it to gain a competitive advantage. For example, a studio with a reputation for making truthful announcements can use it to capture the most profitable release dates. Switching release dates in this case can be costly, as a studio may lose its reputation, giving it a weak position to capture profitable release dates in the subsequent seasons.

These three sources of switching costs work together to dissuade studios from changing preannounced release dates. However, whether switching costs are sufficiently large to make these announcements credible, is ultimately an empirical question. In Section 4, I use a revealed preference argument to show that the cost of switching release dates is indeed substantial.

2.2 Data

2.2.1 Announcements and box office revenues

In many markets, data on product preannouncements is disaggregated, making it difficult to analyze the announcement behavior of firms. A unique feature of the U.S. movie market is the monthly industry magazine, Feature Release Schedule, which publishes the release date announcements of studios. In this paper, I use a novel dataset on release date announcements collected from this industry magazine. At the beginning of each month, Feature Release Schedule publishes information on the scheduled release dates of movies approaching the final stages of the production process. At the end of the month this collected information is published in a summary table in

cally, I downloaded copies of more than 1,800 trailers from the online archive at traileraddict.com and then programatically determined whether each trailer presents a tentative release date of the advertised movie. The collected data shows that more than 40% of trailers announce specific release dates (e.g. “24 December 2016”).

The idea of competitors building reputation over time was first proposed in the influential paper of Kreps and Wilson (1982).

11 As discussed in Section 2, this industry magazine is not the only source from which industry participants may learn about tentative release dates of movies. Therefore, I do not consider release schedules from Feature Release Schedule as a measure of information available to movie distributors. Instead, I see this magazine as a convenient way to collect data on the complete histories of prerelease announcements.

12 Until recent years, Exhibitor Relations collected information about release dates by making phone calls to movie distributors. Nowadays, studios notify Exhibitor Relations about release dates changes through email.
the new issue.

To reconstruct the history of announcements, I digitized the scanned copies of Feature Release Schedule and constructed complete series of monthly announcements made by different distributors. The resulting data contains 57,987 monthly release date announcements for 4,584 films that were released nationwide in the United States between January 1, 1983 and December 31, 2014. I matched this sample of announcements to the data on movie characteristics and the actual box office revenues obtained from the Internet Movie Database (IMDb) and Nash Information Services. The resulting dataset contains weekly observations on the U.S. box-office revenues and number of theaters in which a movie was exhibited for all films in the announcement data. Additionally, for each movie, I observe the official release date, distributor, budget, genre, and MPAA age rating. Note that data on the actual revenues of movies plays a crucial role in my analysis. Absent revenue data, it would be difficult to quantify switching costs of studios as I would not be able to measure the gains from switching release dates. I will return to this point in Section when discussing the main estimation results from the structural model.

Panel A in Table 1 presents summary statistics describing the announcement behavior of studios. A studio makes on average 12.7 announcements for each of its movies, with the first announcement published 9-10 months in advance of the actual release date. The first few announcements from each movie do not typically contain specific release dates, as in “July 2014” or “Summer 2014,” whereas later announcements specify particular dates, e.g. “4 July 2014.” Out of all announcements, 86% reveal specific release dates, while the remaining 14% only contain information about the year, season, or month of release.

Studios change their release dates surprisingly often; indeed, as over 60% of movies in the data switch release dates at least once. This observation seems puzzling given that switching release dates is costly for a variety of reasons. In addition, movies with certain characteristics change their release dates more frequently than others. To illustrate, I regress the switching indicator for a given movie-month combination on different movie characteristics in Table 2. According to

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13 The data for 2000-2014 was obtained directly from Exhibitor Relations in the form of scanned issues of the magazine. I thank Liran Einav for sharing data from the issues published in 1983-1999; this data was previously used in Einav (2010).

14 Prior research typically uses the threshold of 600 screens. I do not have data on the number of screens on which a movie was shown and instead use the information on the number of theaters. According to MPAA’s website, the average theater in U.S. had 3-3.5 screens in 1983; thus, instead of the 600 screens threshold I define nationwide releases as all movies that were exhibited in more than 600/3=200 theaters.

15 Since the sample spans a long period of 32 years, I deflate the box office revenues of movies using the average ticket prices reported on the website of National Association of Theater Owners.

16 The purpose of some announcements is to inform the market about the change of the release date, whereas other announcements simply repeat the release date announced before.
the results, studios reschedule releases of their low-budget significantly more often than those of high-budget films; in addition, minor distributors reschedule more often than major studios. This heterogeneity in switching behavior suggests that major distributors face larger switching costs, especially when releasing high budget films. It is important to emphasize that such asymmetry in switching behavior could also be generated by unobserved heterogeneity of movies, a concern that I address directly in Section 4. Finally, studios in my dataset often change release dates 6-12 months in advance but rarely switch within the last few months before the actual release, implying that switching release dates is relatively easy early during the preparation process but becomes increasingly costly as the scheduled release date approaches.

2.2.2 Production delays

Inferring the cost of switching release dates from announcements is challenging. A naive approach would be to examine the cases when high-demand release dates become available and analyze whether studios capture these profitable dates by rescheduling releases of their movies. This approach, however, cannot identify switching costs, because lack of switching can be driven by the unobserved heterogeneity of release weeks. For example, Thanksgiving week, which is considered to be a lucrative release slot, may become available because of an important sports game scheduled on Thanksgiving weekend. In this case, studios will avoid switching to that week, since any movie released at that time is unlikely to attract a major share of the holiday audience. Failure to account for such week-specific demand shocks can lead to severe overestimation of switching costs.

I solve this identification problem by using a novel dataset on production delays of movies. Major production delays force certain movies to change their release dates, thus vacating release slots. When a highly profitable slot is vacated because of a delay, competing movies should respond by switching to this slot. A studio’s decision not to switch in this case indicates the presence of switching costs.

To analyze studio response to delays, I hand collected the data on major production delays from the main industry magazines including Variety, Hollywood Reporter, and Entertainment Weekly by downloading all articles with keywords such as “delay”, “postponement”, and “release date change” (see Appendix D for details). I then selected specific mentions of movies that postponed release dates for reasons unrelated to competition. The final sample contains 120 delays, the majority of which were due to the injuries of leading actors, bad weather conditions on the set, or simply due to a failure to finish editing before the scheduled release date. For each movie in this dataset, I observe the name of the delayed movie and the release date vacated by this delay. Note that I observe only those production delays which were sufficiently severe to prompt a change in the release date. One concern with this data can be that studios facing production delays may only decide to reschedule
if they find the current release date relatively unattractive. In Section 4, I show through a series of robustness analyses that endogenous decisions to delay the release are unlikely to bias the main results.

3 Simple Model of Announcements

This section develops a simple model capturing the main incentives of movie studios. I develop this model with two main goals in mind. The first one is to develop the intuition for why studios may want to preannounce the release dates, and when such behavior can be optimal. The intuition I develop generates several testable implications, which I analyze empirically in the next section. The second goal of the simple model, however, is to develop a tractable model of competition which serves as a benchmark for the empirical model in Section 5.

3.1 Setup

Suppose two studios \((i = 1, 2)\) are choosing release weeks for their movies, and each studio owns one movie. To simplify exhibition, I will refer to the players of the game as movie 1 and movie 2. The movies choose between two release weeks \((j = 1, 2)\) by playing the following three-stage game. In stage 0, players decide which one of them moves first by tossing a fair coin. Let movie \(L \in \{1, 2\}\) be the designated first mover (“leader”), and let \(F \in \{1, 2\}\) be his competitor (“follower”). In stage 1, players sequentially choose announcements \(c_i \in \{0, 1, 2\}\) following the order of moves established in stage 0. By choosing \(c_i = k (k = 1, 2)\), movie \(i\) announces its plans to release in week \(k\), whereas \(c_i = 0\) implies that movie remains passive and makes no announcements. In stage 2, players sequentially decide on their final release dates \(a_i \in \{1, 2\}\) following the same order of moves as before. If a movie chooses release date that does not match the announcement \(c_i \neq 0\), it has to pay a fixed switching cost \(\gamma_i > 0\). Once the final decisions are made, movies receive final payoffs, and the game stops.

Because my empirical strategy relies on the analysis of how studios respond to the production delays of their rivals, it is important to explicitly include delays in the model. I assume that, at the beginning of stage 2, each movie experiences a major production delay with exogenous probability \(\mu\), in which case it is released neither in week 1 nor in week 2.\(^{17}\) If only one of two movies gets delayed, the other one plays a monopoly version of the game by unilaterally choosing the final release date.

\(^{17}\)Here I assume that the probability of experiencing a production delay does not depend on movie’s characteristics. Relaxing this assumption does not affect the main predictions of the model and has little effect on the estimates from the empirical model.
release week and collecting final payoffs. The payoff movie receives after having experienced a delay is normalized to zero.

The payoffs of players consist of two main parts: switching costs incurred during the game, if any; and final payoffs, which I interpret as box office revenues of movies. Specifically, suppose vectors \( c = (c_1, c_2) \) and \( a = (a_1, a_2) \) summarize the announcements and final release dates of two movies. Additionally, assume two movies have qualities \( \theta_1 \) and \( \theta_2 \), so that the movie with larger quality \textit{ceteris paribus} attracts a larger number of moviegoers. The payoff of movie \( i \) from releasing in week \( j \) is assumed to be:

\[
\pi_{ij}(a, c) = M_j \cdot s_i(\theta_1, \theta_2, a_{-i}) - \gamma_i \cdot 1 \{c_i \neq 0, c_i \neq a_i\} + \varepsilon_{ij} \tag{1}
\]

The first part of this expression represents box office revenues of a movie, where \( M_j \) is a number of consumers who are willing to watch movies in week \( j \), and \( s(\theta_1, \theta_2, a_{-i}) \) is a share of these consumers captured by movie \( i \). This share equals \( s(\theta_1, \theta_2, a_{-i}) = \theta_i / (1 + \theta_i + \theta_{-i}) \) when movies are released in the same week \((a_1 = a_2)\), and \( s(\theta_1, \theta_2, a_{-i}) = \theta_i / (1 + \theta_i) \) when movies choose to release on different weeks \((a_1 \neq a_2)\).\(^{18}\)

The demand in the movie industry is highly seasonal, which makes some release weeks substantially more attractive than others. To capture this asymmetry, I assume that potential demand is higher in week 1, so that \( M_1 > M_2 \). Additionally, I eliminate uninteresting equilibria by assuming that the demand in week 1 is not sufficiently high to accommodate both movies, i.e. \( M_1 \theta_i / (1 + \theta_i + \theta_i) < M_2 \theta_i / (1 + \theta_i) \). This last inequality suggests that a movie would rather shift its release to low-demand week 2 than share high-demand week 1 with its competitor. By making this assumption, I ensure that movies can potentially benefit from preannouncing their release dates. By announcing to release on week 1, a movie can improve its chances to capture the largest of two markets, at the same time dissuading its competitor from releasing in the same week.

The second part of the payoff function in (1) indicates that a movie have to pay a switching cost \( \gamma_i \) in case its final release date \( a_i \) does not match the prior announcement \( c_i \). As discussed earlier, this switching cost represents a combination of renegotiation costs, reaction of consumers to release date changes, and reputational costs. Finally, the last part in (1) is a week-specific profit shock \( \varepsilon_{ij} \). I interpret \( \varepsilon_{ij} \) as unanticipated supply-side shocks that make some release weeks more attractive than others. The shocks \( \varepsilon_{ij} \) are observed only movie \( i \) in stage 2; whereas in stage 1, players only know that \( \varepsilon_{ij} \) are iid across players and weeks and follow the distribution \( F_\varepsilon(\varepsilon) \).\(^{19}\)

\(^{18}\)One can interpret these shares as coming from a logit demand model, where each of \( M_j \) consumers chooses which of two movies to watch, and utility from watching movie \( j \) equals \( u_j = \log(\theta_j) + \omega_j \).

\(^{19}\)In this model, movies face a trade-off between committing to a certain release date and remaining flexible. Whereas preannouncing release week helps movie to capture the week with the highest demand, remaining flexible insures...
3.2 Best Response Functions

To measure switching costs $\gamma_i$ from the data, we need to first understand how switching frictions affect strategic behavior of studios. To this end, I derive three lemmas characterizing how each studio $i$ responds to an increase in its own switching cost $\gamma_i$, increase in competitor’s switching cost $\gamma_{-i}$, and how it reacts to competitors’ production delays. This section states lemmas without proofs and develops the key intuitions, while formal proofs are delegated to Appendix A.

Lemma 1. Suppose neither of two movies delays. If movie $i$ announces release week $j$ in stage 1, the probability that it will switch to another week $j' \neq j$ in stage 2 decreases in switching cost $\gamma_i$. That is, if $c_i \neq 0$, then $\partial P(a^*_i \neq c_i | c_i, c_{-i}) / \partial \gamma_i < 0$ for any $c_{-i}$ and $i = 1, 2$.

This lemma suggests that whether announcements of movie $i$ are credible depends critically on its switching cost. When switching cost is small, announcements $c_i$ are not credible; therefore, they have little effect on the final choices of release dates $a_1$ and $a_2$. In contrast, when switching cost is large, preannouncing release week $c_i$ generates a credible commitment, making it prohibitively costly for studio to switch to another week in stage 2.

The next lemma shows that, apart from affecting incentives of movie $i$, announcement $c_i$ may also affect strategic incentives of $i$’s competitor.

Lemma 2. Suppose neither of two movies delays. If a movie $i$ commits to release on week $j$ in stage 1, the probability that its competitor chooses the same release week $j$ in stage 2 decreases. That is, for $i = 1, 2$ and for any $c_2$ we have $\partial P(a^*_i = c_i | c_i = 1, 2) / \partial \gamma_i < 0$.

According to this result, preannouncing week $c_i$ may deter competitor from choosing the same release week. This deterrence effect arises because demand on a given week is relatively small, making it unprofitable for players to release on the same week. Therefore, if movie $i$ credibly commits to release on week $j$, its competitor is forced to shift its release in order to avoid detrimental competition. As in the previous lemma, the deterrence effect arises as long as switching cost of movie $i$ is sufficiently large; if this cost is small, commitments of movie $i$ lack credence and do not affect strategic incentives of its competitor in stage 2.

When put together, lemmas 1 and 2 suggest that movies may benefit from preannouncing their release strategies. By announcing a release on the high-demand week 1, a movie can capture the largest of two audiences, while also deterring its competitor from releasing on the same week. However, although such deterrence strategies can be effective in theory, whether studios actually
adopt them crucially depends on the magnitudes of switching costs $\gamma_i$ and on marginal gains from capturing the high-demand release week. This observation suggests that measuring profitability of different release weeks and estimating switching costs is crucial if we want to better understand the strategic incentives of movie studios.

The lemmas described so far characterize best response functions of players in the subgames where none of two players delays. By contrast, the next lemma suggests how movie should respond to the unexpected production delay of its competitor.

**Lemma 3.** Suppose the competitor of movie $i$ preannounces a release on week 1 but later exits the game due to the unexpected production delay. The probability that movie $i$ shifts its release to the vacated week 1 in stage 2 is increasing in movie $i$’s quality $\theta_i$ and decreasing in its switching cost $\gamma_i$.

Put another way, if a movie has announced a release on the high-demand week but exits the game due to production problems, competing movies capture the vacated time slot by rescheduling their releases. Whether competing movies will actually reschedule depends on two main characteristics: movie’s quality and switching costs. Movies with higher quality $\theta_i$ are more likely to capture the vacated slot, as they can capture a larger share of audience $M_1$ and therefore have more to gain from rescheduling. In addition, having higher switching cost $\gamma_i$ dissuades movie from rescheduling its release, regardless of potential gains in profits. Thus, vacated release slots are often captured by movies that have relatively high quality $\theta_i$ and relatively low switching cost $\gamma_i$.

### 3.3 Equilibrium and Switching Costs

To analyze how the outcomes of this game depend on switching costs, I solve for the unique Subgame Perfect Nash Equilibrium for different values of $\gamma_1$ and $\gamma_2$. An important feature of the equilibrium is that its outcomes critically depend on the magnitudes of switching costs $\gamma_1$ and $\gamma_2$, but are relatively insensitive to the exact order in which players move. When $\gamma_1 = \gamma_2 = 0$, announcements made in stage 1 are not binding; therefore, the actions chosen in stage 1 do not affect the final choice of release dates. In this case, movies play a Stackelberg game in which they pick release dates sequentially with the randomly chosen first-mover. By contrast, when $\gamma_1 \to \infty$ and $\gamma_2 = 0$, movie 1 can credibly commit to a certain release date, because its announcements are fully binding. This commitment power effectively makes movie 1 a Stackelberg leader, as it can choose release week first regardless of the order of moves. A symmetric argument implies when $\gamma_2 \to \infty$ and $\gamma_1 = 0$ when movie 2 becomes a Stackelberg leader. Appendix B provides a numerical example illustrating how the equilibrium changes with the values of switching costs.
This structure of the equilibrium implies that studios with relatively high switching costs have a significant competitive advantage. For example, if major studios in the U.S. movie industry have high switching costs, they can essentially choose release dates for their movies first, leaving only unprofitable dates to minor distributors. In contrast, if switching costs of minor distributors are larger than those of major studios, the first-mover advantage is then enjoyed by minor distributors. In Section 5, I further explore these alternatives by estimating switching costs and establishing how these costs differ across distributors or across movies with different characteristics.

4 Empirical Evidence of Commitment

The results from the simple model illustrate that if switching costs are sufficiently high, public announcements may have a substantial effect on the final release dates of movies. Moreover, whether studios win or lose from the presence of these announcements critically depends on the relative magnitude of switching costs. My main goal in this section is to verify that the U.S. movie studios indeed face substantial costs when rescheduling release dates. I first discuss the empirical strategy I follow to identify switching costs. I then show empirical evidence suggesting that studios can easily change the release dates of their movies 5-8 months ahead of the nationwide release without incurring costs, whereas last-minute changes are difficult and require substantial switching costs.

4.1 Switching Release Dates is Costly

**Empirical strategy.** A somewhat naive approach to evaluating switching costs would be to examine the general tendency of studios to change release dates. For example, we could study the cases where a high-demand release date (e.g., holiday weekend) became available and analyze whether competing studios shifted the releases of their movies to a vacated date. If studios rarely did so, we could conclude that they had already committed to certain release dates and found it costly to reschedule. However, the unobserved demand shocks that initially vacated a given release week could have also made this week unattractive to other studios (e.g., a big sports event may discourage all studios from releasing movies at that time). In this case, ignoring these unobserved shocks may lead to substantial overestimation of studios’ switching costs.

To circumvent this problem, I use data on the unexpected production delays of movies. When a movie experiences a major production delay, it is usually forced to postpone its release date by several months. These postponements often vacate highly profitable release slots, which can then be occupied by competing studios. My empirical strategy is to analyze whether studios respond to unexpected delays of competitors by shifting their releases to the vacated slots. Specifically,
my main goal is to determine whether studios are reluctant to switch to the vacated slots even when doing so increases their expected revenues. If studios rarely respond to rival’s delays by rescheduling release dates of their movies, I rationalize this behavior by assuming that they face substantial switching costs.

The main advantage of analyzing production delays is that it helps to understand if a release date was changed due to movie-specific production problems, or if it was rescheduled in response to market-wide demand shocks. By concentrating on movie-specific production shocks, I can effectively focus on cases where studios vacate highly profitable release slots for reasons unrelated to week-specific demand shocks. In this case, we can be relatively confident that switching decisions of competing studios are not driven by unobserved demand shocks; instead, they are mostly led by the trade-off between increasing box office revenues and saving on switching costs.

To formalize this empirical strategy, I first need to define relevant markets. To this end, for each of 120 production delays in the data, I identify all movies that were eventually released within three weeks from the time slot vacated by the delay. Defining this group of movies as a market, I obtain a sample of 120 markets spread across 32 years of the data. The resulting sample is used to estimate the model in which the decision of the studio holding movie $i$ to switch to the vacated time slot in month $t$ is modeled as

$$SwitchToVacated_{it} = \alpha + \gamma \cdot RivalDelays_{it} + \delta \cdot RivalDelays_{it} \times MonthsToRelease_{it} +$$

$$+ \lambda \cdot MonthsToRelease_{it} + x'_i \beta + \varepsilon_{it}$$

(2)

where $SwitchToVacated_{it}$ is an indicator that movie $i$ switched to the vacated slot; $RivalDelays_{it}$ is a dummy variable indicating whether one of the competing movies experienced production delay in month $t$; $MonthsToRelease_{it}$ is the number of months left until the official release of the movie; and $RivalDelays_{it} \times MonthsToRelease_{it}$ is the interaction capturing that making last-minute changes in release dates is more costly than rescheduling movies several months in ahead of the planned release. Note that the general tendency of studios to switch release dates changes over time even in seasons with no production delays. To control for this change, the benchmark specification in (2) includes a linear time trend $\lambda \cdot MonthsToRelease_{it}$, while some other specifications control for a nonparametric time trend by including month dummies.

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20 Although the choice of the three-week window is somewhat arbitrary, experimenting with alternative definitions of a market have do not affect the main qualitative results.

21 Note that $SwitchToVacated_{it}$ can be equal to one both before and after the month in which one of competitors experienced a production delay.

22 The release dates used to compute $MonthsToRelease_{it}$ coincide with the official release dates of movies observed in the data.

23 In the data, the unconditional switching probability first increases until 2-4 months before the official release.
Since movies experiencing production delays in my data have on average larger budgets and are more likely to be produced by major studios, I control for the observed characteristics of movies by including a vector of movie characteristics $x_i$. This vector $x_i$ includes the budget, distributor, genre, age rating, and release season (e.g. winter holidays 2014), apart from some specifications in which I replace $x_i'\beta$ with movie fixed-effects.

Of particular interest are coefficients $\gamma$ and $\delta$ in equation (2). A large value of $\gamma$ indicates that studios often respond to competitors’ delays by switching to vacated time slots, whereas a small value of $\gamma$ suggests that studios face substantial switching costs. In addition, coefficient $\delta$ determines whether the probability of switching changes over time; for example, $\delta > 0$ implies that studios find it more costly to make last-minute changes than to change release dates several months ahead of the upcoming season.

To estimate the model in (2), I rely on four main identifying assumptions: (a) studios can not anticipate future delays of competitors; (b) studios respond to rivals’ delays in the same month that the delay occurred; (c) delays occur due to movie-specific production problems; as a result, a production delay of one movie does not directly affect the profits of competing films; and (d) decisions of studios to delay their releases in response to production problems are unrelated to the unobserved profitability of vacated time slots. Assumptions (a) and (b) justify the fact that the model in (2) does not include lagged values of $RivalDelays_{it}$, while assumptions (c) and (d) effectively serve as an exclusion restriction, ensuring that production delays of movies affect actions of their competitors only though the channel of competition. I discuss these assumptions in detail in the end of this section after presenting the main estimation results.

**Estimation results.** Table 3 presents the estimation results from the benchmark model. The first column reports the results from the specification with linear trend but without controlling for observed movie characteristics. Although the key estimates in this specification are relatively noisy, their magnitudes are economically meaningful. Specifically, the estimates imply that when the delay occurs more than 8 months before the scheduled release, a studio is at least 60% more likely to reschedule releases of its movies to the vacated time slot compared to the case of no delay. In contrast, when the delay occurs within one month before the scheduled release, a studio is only 6.8% more likely to reschedule. Hence, the estimated coefficients suggest that studios are more responsive to production delays of competitors when the delay occurs several months ahead of the scheduled release.

The estimates in the benchmark model provide a natural starting point. However, this bench-
The mark model assumes that the time trend is linear and the probability that studios respond to the delays of their rivals changes linearly with time. These assumptions may not hold, especially considering that the unconditional probability of switching in the data follows an inverse U-shape, suggesting the need for a nonlinear time trend. To relax the linearity assumption, I extend the benchmark specification by including a nonparametric time trend and by interacting this trend with the $RivalDelays_{st}$ variable. The results from the extended model are presented in columns 2-5 of Table 3. The main difference between columns is a set of control variables used for estimation: column 2 reports the estimation results without controls; column 3 controls for observable characteristics of movies such as the genre and the budget; column 4 additionally controls for season fixed-effects, capturing the fact that switching behavior may differ across different months of the year (e.g. more rescheduling during the winter holidays); and column 5 replaces observable characteristics with movie fixed-effects. In what follows, I focus on the estimates from column 5, which corresponds to my preferred specification.\footnote{Including fixed-effects allows to control for the time-invariant quality of a movie. I prefer this specification over the one with observed movie characteristics, because production budget tends to be a relatively noisy measure of movie’s quality.}

I make two main observations based on these estimates. First, consistent with our observations above, the estimated month fixed-effects reveal that the general propensity of studios to switch release dates follows an inverse U-shaped trend. This finding emphasizes that controlling for a flexible time trend is indeed crucial in these specifications. Second, when a production delay occurs 7-8 months ahead of the season, studios become 81.1% more likely to switch to a given release week when that week is vacated by a rival’s delay. However, when the delay occurs during the last four months, the probability of switching does not increase; in fact, the corresponding estimates are even negative (although not statistically significant). This fading response suggests that studios gradually commit to the release dates of their movies: they can easily reschedule their release dates early in the process at no cost, but are reluctant to make last-minute changes. Overall, these results are consistent with the theory that studios face non-trivial switching costs which tend to be low at first but become substantial within a few months before the season of releases.

4.2 Discussion of Identifying Assumptions

Delays are unanticipated. In the analysis presented thus far I relied on several identifying assumptions. One such assumption is that studios cannot anticipate production delays of competitors and only react after these delays have been officially announced in the media. This assumption can be violated if studios can predict production problems of competitors or can learn about these problems in advance, e.g., from private conversations or news sources not covered in my data. However,
several observations suggest that this anticipation effect plays little role in my application. First, most of major delays I analyse occurred by reasons that are hard to predict such as an injury of the leading actor or schedule conflicts in the film crew. For example, it was probably hard to predict that Russell Crowe would dislocate his shoulder, an injury that delayed the release of *Cinderella Man* by four months. Similarly, it was difficult to anticipate that Gore Verbinski was not available to promote his new movie *The Weather Man* due to the conflicts in his busy schedule. To the extent that these events are random and cannot be predicted by competitors, we should not see studios reacting to production delays ahead of time.

It is still possible that studios learn about production issues of competitors through other means not captured in my data. Because I cannot test this effect directly, I investigate it by performing a placebo test, in which I include both forward and backward lags of $\text{RivalDelays}_{it}$ in the equation (2). As before, the regression controls for a time trend to account for the general trend in rescheduling activities. The estimates from this modified regression are presented in Table A1 but to ease interpretation I present the estimates graphically in Figure A2. As this figure suggests, studios do not react to production delays in months preceeding the official announcement; in fact, the coefficients on the lagged values of $\text{RivalDelays}_{it}$ are all small in magnitude and statistically undistinguishable from zero. In contrast, studios exhibit a clear response on the month when the delay was announced in the news. This pattern is reassuring as it suggests that, even if studios anticipate production problems of competitors, the anticipation effect does not appear to be first-order in my application.

**Decisions to delay are exogenous.** Another crucial assumption is that, when studios experience major production problems, their decisions to delay the release of a troubled movie do not depend on the initial release plans. This assumption can be violated if, for example, studios are reluctant to move the release dates of movies scheduled to open in a lucrative time slot, e.g. on a holiday weekend. To investigate whether this selection channel is empirically relevant, I re-estimate the equation in (2) controlling for the indicator that the delayed movie was initially scheduled to be released on a holiday week. The resulting estimates are presented in Table A2 where I compare estimated coefficients with the ones from the benchmark regression. Comparing the results in two columns reveals that controlling for holiday dummies does not change qualitative results; in fact, the magnitudes of estimated coefficients are almost identical in two specifications. Although I cannot perfectly control for the unobserved profitability of vacated slots using holiday dummies, the results from Table A2 suggest that endogeneity of rescheduling decisions is unlikely to bias the key estimates.
Production problems are idiosyncratic. When estimating the equation in (2), I also assume that production delays occur by idiosyncratic reasons unrelated to general market conditions. Put another way, production problems of a given movie are uncorrelated with any difficulties that studios might face regarding other films. This need not be true in general, and one can find several examples of historical events that affected production schedules of multiple movies at the same time. A prominent example of such event is the strike of the Recession in 2008, which induced several studios to reduce funding allocated to risky movies, thus simultaneously affecting release schedules of several distributors. However, I note that my data on production delays does not include movies that were delayed due to market-wide shocks; instead, the current sample is centered around events specific to a particular movie, such as an injury of the leading actor or production issues experienced during the editing process. Hence, because of the way my sample is constructed, it is somewhat unlikely that production problems are systematically correlated across different movies.

5 Empirical Model of Announcements

The results in the previous section illustrate how studios become increasingly reluctant to switch release dates of movies as they approach the season of releases. Although this observation suggest that switching costs of studios increase over time, the reduced-form results presented thus far do not allow to recover the magnitudes of these switching costs, making it impossible to analyze the counterfactual scenario without preannouncements. In this section, I show how extending the simple model from Section 3 allows to explicitly estimate search costs of studios as a function of time, identities of studios, and movie characteristics.

5.1 Extended Model

Consider a game in which $K$ movies ($k = 1, \ldots, K$) are choosing among $W$ release weeks ($w = 1, \ldots, W$). They play a sequential game where each movie has several opportunities to adjust its release plans. Before starting the game, players randomly choose the order of moves $\delta$ by taking a draw from uniform distribution of potential orders. Formally, $\delta : \{1, \ldots, K\} \rightarrow \{1, \ldots, K\}$ is a permutation such that the player $\delta_1$ moves first, the player $\delta_2$ moves second, and so on until the player $\delta_K$. Once the order of moves is known, the game proceeds in $R$ consecutive rounds. In round 1, players sequentially announce their release weeks following the order $\delta$. First, the player $\delta_1$ chooses a release week $a_{\delta_1} \in \{0, 1, \ldots, W\}$, where the action $a_{\delta_1} = 0$ corresponds to an outside option. This outside option should be interpreted as a decision not to make an announcement at

\[25\text{With some abuse of notation, let } \delta_k \text{ denote the identity of a player who moves } k\text{th, so that } \delta_k = \delta(k).\]
all or choose a release week other than 1, \ldots, W. Next, the player $\delta_2$ makes a similar choice by announcing a release week $a_{\delta_2}$, then player $\delta_3$ announces release week $a_{\delta_3}$, and so on. Once players come a full circle, the game proceeds to round 2 where players may change the previously announced release dates by making revisions in the same order $\delta$. These rounds of sequential announcements continue until the end of round $R$, after which the game stops and the choices of players $a_{\delta_1}, \ldots, a_{\delta_k}$ made in the last round $R$ become final release dates of movies.

The key feature of the game is the ability of players to revise the previously announced release weeks. Each player $k$ might in principle revise his release week in each round, but has to pay a switching cost $\gamma_k \geq 0$ for each revision. I assume that the switching cost $\gamma_k$ weakly increases over time, reflecting that changing release dates becomes more difficult as players approach the season of releases. In addition to paying switching costs, players receive choice-specific payoff shocks $\varepsilon_k(a)$, which I interpret as minor production shocks that change relative attractiveness of different release weeks. These shocks $\varepsilon_k(a)$ represent private information of player $k$; they are observed only by player $k$ immediately before making a choice, but are unobserved to the competitors of $k$. All players have rational expectations and know that shocks $\varepsilon_k(a)$ follow iid extreme value distribution with variance $\pi^2 \sigma^2_{\varepsilon}/6$.

As in the previous section, the identification of switching costs in this extended model relies on the variation generated by major production delays. Therefore, it is important to incorporate production delays into the current model of competition and allow players to optimally respond to the delays of competitors. To this end, I assume that at the beginning of each round $r$, each movie delays with probability $\mu$. The delays of different players are assumed to be independent from each other. Additionally, these delays are unanticipated and do not correlate with payoff-related variables or week-specific shocks $\varepsilon_k(a)$. Although these assumptions may seem strong, the discussion in the previous section suggests that they are generally consistent with the data. When the player $k$ delays, he switches to the outside option $a_k = 0$ and pays a fixed cost $\gamma_k$ in case he has already announced his release week before. Once delayed, the player must choose the outside option $a = 0$ until the end of the game, so major delay can be interpreted as an absorbing state.

The final payoffs of the game resemble those in Section 3. In particular, the final payoff of the player $k$ consists of three parts: switching costs $\gamma_k$ incurred throughout the game; production shocks $\varepsilon_k(a)$ accumulated in all rounds; and box office revenues of movie $k$, denoted by $R_k(r, \theta)$, where $r = (r_1, \ldots, r_K)$ are the final release dates of movies. As I explain in detail later, in my application, the function $R_k(r, \theta)$ depends on a vector of parameters $\theta$ that capture the qualities of competing movies, demand for movies on different weeks, decay of revenues for a given movie across weeks, and the degree to which releasing an additional movie expands the market. The payoff from choosing the outside option is normalized to zero, so $R_k(r, \theta) = 0$ if $r_k = 0$. Finally, I assume that
the payoff functions $R_k(r, \theta)$ are perfectly observed by all players.

5.2 Solution

The model described above can be classified as sequential game with imperfect information. I solve this game using the concept of Perfect Bayesian Nash Equilibrium. To describe the solution, I start by introducing additional notation. First, it is useful to introduce a time index $t$ identifying moves of different players. In particular, I assume that the game proceeds in stages $t = 1, \ldots, T$ with $T = RK$; hence, stages $t = 1, \ldots, K$ occur in round $r = 1$, stages $t = K + 1, \ldots, 2K$ occur in round $r = 2$, and so on. Figure X summarizes the timing of the game and clarifies the relationship between rounds $r$ and periods $t$. Second, let $L(t)$ denote the identity of the player who moves in stage $t$ according to the order $\delta$ (“leader”), and let $F(t)$ be a set of $L(t)$’s competitors (“followers”).

Finally, to define the state vector, let $r_t = (r_{1t}, \ldots, r_{Kt})$ be a vector of current release dates of movies in stage $t$, which correspond to the most recent announcements of players. Also let $p_t = (p_{1t}, \ldots, p_{Kt})$ be a vector describing the current production status of movies in stage $t$, where $p_{kt}$ equals one if movie $k$ has been delayed before stage $t$ and zero otherwise. The state vector $s_t$ is defined as a combination of the current release dates, the production status of movies, and the order of movies, so $s_t = (r_t, p_t, \delta)$.

The state $s_t$ evolves according to a simple stochastic rule. The order of moves $\delta$ is realized before the start of the game and remains the same throughout all stages. Next, the release dates $r_t$ are determined by the most recent announcements of players. For example, the current release date of the player $L(t)$ who moves in stage $t$ corresponds to the date he chose in the previous round of announcements, so $r_{L(t),t} = a_{L(t),t-K}$. Finally, production status of movies $p_t$ randomly changes at the beginning of each round $r$. Specifically, at the beginning of each round, movie $k$ delays with probability $\mu$ if it has not yet experienced a delay in the previous periods. The delay status remains unchanged if the movie has already been delayed in the past.

The game has a finite horizon, so I solve for the unique equilibrium using backwards induction. In stage $T + 1$, when the game has already finished, the value of player $k$ simply equals the expected box office revenue of his movie. Formally, we can express this value as $V_{k,T+1}(s_{T+1}) = R_k(r_{T+1}, \theta)$ for $k = 1, \ldots, K$. We can now recursively specify the value function in earlier stages $t < T + 1$. Let the function $v_{L(t),t}(a, s_t)$ denote the value of player $L(t)$ from choosing release week $a$. This choice-specific value can be expressed as

$$v_{L(t),t}(a, s_t) = -\gamma_{L(t)}(t) \cdot 1 \{a \neq r_{L(t),t}, r_{L(t),t} \neq 0\} + \int V_{L(t),t+1}(s_{t+1})dF(s_{t+1}|s_t, a)$$
where the first component represents switching costs paid when the current action does not match
the previous announcement \((a \neq r_{l(t),t}, r_{l(t),t} \neq 0)\); and the second component captures the
discounted continuation value. In stage \(t\), the player \(L(t)\) learns the realizations of choice-specific
shocks \(\varepsilon_{kt}(a)\) and chooses announcement \(a\) that maximizes the sum \(v_{L(t),t}(a, s_t) + \varepsilon_{L(t),t}(a)\). Hence,
before \(\varepsilon_{kt}(a)\) become known, the value of player \(k\) in state \(s_t\) is

\[
V_{L(t),t}(s_t) = E_{\varepsilon} \max_{a \in A} \left( v_{L(t),t}(a, s_t) + \varepsilon_{L(t),t}(a) \right) = \sigma_{\varepsilon} \ln \left( \sum_{a \in A} \exp \left( \frac{v_{L(t),t}(a, s_t)}{\sigma_{\varepsilon}} \right) \right)
\]  

(4)

and the player chooses announcement \(a\) with probability

\[
P_{L(t),t}(a|s_t) = \frac{\exp \left( \frac{v_{L(t),t}(a, s_t)}{\sigma_{\varepsilon}} \right)}{\sum_k \exp \left( \frac{v_{L(t),t}(k, s_t)}{\sigma_{\varepsilon}} \right)}
\]

(5)

where both expressions use the assumption that shocks \(\varepsilon_{kt}(a)\) are distributed iid extreme value.
Finally, the players \(F(t)\) remain idle in stage \(t\). The value of each player \(f \in F(t)\) from being in
state \(s_t\) equals an expected continuation value, where the expectation is over the announcement of
\(L(t)\):

\[
V_{f(t),t}(s_t) = \sum_{a \in A} P_{L(t),t}(a|s_t) \int V_{f(t),t+1}(s_{t+1})dF(s_{t+1}|s_t, a)
\]

(6)

As a whole, equations (3), (4), and (6) recursively define the values functions of players in all
possible states \(s_t\); whereas the expression in (5) gives related choice probabilities. Note that these
expressions fully describe the unique solution of the game for any possible order of moves \(\delta\).

5.3 Parametrization

5.3.1 Final Payoffs \(R_k(r, \theta)\)

The function \(R_k(r, \theta)\) captures box office revenues of movie \(k\) for a given configuration of release
dates \(r\) and demand parameters \(\theta\). This revenue function plays a crucial role in the game as it
determines which release weeks attract most consumers, how many movies can fit in these weeks,
and whether studios find may find it profitable to make release date commitments. To provide an
accurate measure of expected revenues, the function \(R_k(r, \theta)\) must capture three main features of
the market: asymmetric demand on different release weeks (e.g. national holidays generate the
highest demand); asymmetric qualities of competing movies; and the fact that studios care about
cumulative renevues collected by their movies during the 8-10 week period of exhibition.
To capture these features, I use a nested logit demand model proposed in \textit{Einav (2007)}. In this demand model, the revenue $R_k(r, \theta)$ of movie $k$ equals the cumulative sum of box office revenues obtained during a $H$ week exhibition period:

$$R_k(r, \theta) = \text{Price} \cdot \text{MarketSize} \cdot \sum_{\tau=r_k}^{H} s_{k\tau}(r, \theta)$$

where $s_{k\tau}(r, \theta)$ is a market share of movie $k$ in week $\tau$, defined as

$$s_{k\tau} = \frac{\exp\left(\frac{\alpha_{\tau} - \lambda(\tau - r_k) + q_k + \xi_{k\tau}}{\pi}\right)}{D_{\tau} + D_{\tau}^{1-\pi}}$$

$$D_{\tau} = \sum_{j \in J_\tau} \exp\left(\frac{\alpha_{\tau} - \lambda(\tau - r_j) + q_j + \xi_{j\tau}}{\pi}\right)$$

In this expression, $\alpha_{\tau}$ is a week fixed-effect measuring demand on different release weeks $\tau$; $r_k$ is the release week of movie $k$; $t - r_k$ is the number of weeks passed since the release of movie $k$; and $\pi$ is a market expansion parameter measuring the degree to which newly-released movies attract new consumers to the market. The parameter $\lambda$ can be interpreted as a rate of decay of movie’s quality, and $\xi_{j\tau}$ captures any deviation from the common decay pattern. The term $q_k$ is the fixed-effect of movie $k$, which I will call movie’s “quality” to simplify discussion.

One attractive feature of the model is its ability to separately identify demand on different weeks $\alpha_{\tau}$ and the qualities of movies $q_k$. This feature helps construct a more precise measure of profitability than the one obtained from the realized industry revenues. The model can also generate quality estimates $q_k$ that will prove useful in the subsequent analyses, as they allow to control for the unobserved heterogeneity of movies and help me study commitment behavior of films as a function of their consumer appeal.

### 5.3.2 Switching Costs $\gamma_k(t)$

To complete the model, I still need to specify the functional form for switching costs $\gamma_k(t)$. From the results in Section 4 recall that switching costs normally increase over time, tend to be larger for high-quality movies than for low-quality films, and appear to be larger for major distributor rather than minor studios. Following these observations, I parametrize switching costs as

$$\gamma_k(t) = \exp(\gamma_0 + \gamma_1 t + \gamma_2 q_k + \gamma_3 x_k)$$

23
where $\gamma_0$ defines the baseline level of switching costs; $\gamma_1$ captures the linear time trend (we expect $\gamma_1 > 0$); $\gamma_2$ captures dependence of switching costs on movie’s quality $q_k$; and $\gamma_3$ allows switching costs to be correlated with characteristics $x_k$ such as distributor’s identity.

### 5.4 Estimation strategy

Suppose the data contains information on $M$ markets ($m = 1, \ldots, M$) and includes the history of release dates $S^m$, evolution of movies’ production status $P^m$, and characteristics of movies competing in each market, $X^m = (x_1, \ldots, x_K)$. Let $\omega = (\theta, \gamma, \sigma_\varepsilon, \beta)$ to be a vector summarizing structural parameters to be estimated, where $\theta = (\alpha, \lambda, \pi, q)$ is a vector of demand parameters, $\gamma = (\gamma_0, \gamma_1, \gamma'_2)$ includes switching cost parameters, $\sigma_\varepsilon$ represents the standard deviation of random shocks, and $\beta$ is the probability of delay. The goal of estimation is to recover structural parameters $\omega$ from the data $\{S^m, P^m, X^m\}_{m=1}^M$.

The estimation proceeds in two steps. First, I estimate demand parameters $\theta$ using data from an auxiliary dataset on box office revenues of movies. Since nested logit model admits simple estimation, this step is computationally light. Second, I estimate supply parameters $\gamma, \sigma_\varepsilon$, and $\beta$ using data on the pre-release announcements. To this end, I pre-estimated probability of $\beta$ directly from the frequency of production delays in the data, and then estimate the remaining structural parameters through Maximum Likelihood.

#### 5.4.1 Step I. Estimation of Demand Parameters

To estimate the demand model, I invert the market shares in (7) and estimate parameters $\theta$ using the within-group regression with instruments as in Berry (1994). I assume that $MarketSize_m$ in each market is equal to the population of the United States during that period, and I measure ticket price $Price_m$ using the average admission prices reported on the website of the Motion Picture Association of America (MPAA). Because estimation of demand is not a primary focus of this paper, I delegate the details to the Appendix A. An interested reader may refer to Einav (2007) for further details of estimation and identification.

#### 5.4.2 Step II. Estimation of Supply Parameters

In my application, I do not fully observe the history of release dates $S^m$, as the dataset contains only snapshots of scheduled release dates at the beginning of each month. Hence, the data only tells me whether studios revised their release dates during a given month, but it does not tell me in which order studios made these revisions. To circumvent this problem of missing data, I assume that each month in my data corresponds to one round of announcements, implying that the data contains
information on release dates at the beginning of each round \( r \). The history of announcements can then be expressed as \( S^m = (r_1, r_1+K, \ldots, r_1+RK) \), where \( r_1 \) contains release dates at the beginning of round 1; \( r_{1+K} \) – release dates at the beginning of round 2; and \( r_{1+RK} \) describe the actual release dates of movies. Note that for a given order of moves \( \delta \), we can impute the announcements made by players within each month, which we denote as \( \hat{A}^m(\delta) = (\hat{a}_1(\delta), \ldots, \hat{a}_T(\delta)) \). Additionally, we can recover the corresponding history of states \( \hat{S}^m \), denoted as \( \hat{S}^m(\delta) = (\hat{s}_1(\delta), \ldots, \hat{s}_T(\delta)) \). This observation suggests that we can first specify likelihood of the data conditional on the order of moves \( \delta \), and then take expectation with respect to the random order \( \delta \) to compute the unconditional likelihood.

To specify the conditional likelihood, recall that the expression in (5) describes choice probabilities of players in all possible states. Therefore, the likelihood of observing history of announcements \( A^m \) given the order of moves \( \delta \) and the data \( (P^m, X^m) \) equals

\[
L^m(\hat{A}^m(\delta)|P^m, X^m, \delta, \omega) = \prod_{t=1}^{T} P^m_{(\hat{a}^m_{L(t),t}|\hat{s}^m_{L(t),t}, X^m)}
\]

By integrating the order of moves \( \delta \) out of this function, we obtain the unconditional likelihood for the observed history of release dates in market \( m \)

\[
L^m(S^m|P^m, X^m, \omega) = \frac{1}{\delta!} \sum_{\delta} L^m(\hat{A}^m(\delta)|P^m, X^m, \delta, \omega)
\]

This step involves imputing announcements \( \hat{A}^m(\delta) \) and states \( \hat{S}^m(\delta) \) and re-computing the conditional likelihood in (8) for each of \( \delta! \) possible orders. Finally, the log-likelihood function for all markets simply equals to the sum of the log-likelihoods across individual markets

\[
\log L(S|P, X, \omega) = \sum_{m=1}^{M} \log L^m(S^m|P^m, X^m, \omega)
\]

I estimate parameters \( \omega \) using the Maximum Likelihood approach, where I re-compute choice probabilities (5) for each new guess of parameters and obtain estimates of \( \omega \) by maximizing the expression in (10).

### 5.5 Identification

This section provides an informal discussion of identification. The identification argument resembles the one discussed in Section 4 and proceeds in two steps. First, I use information on the final release dates of movies together with the demand function \( R(r, \theta) \) to identify the standard deviation of
production shocks $\sigma_\varepsilon$. Second, I study the response of players to production delays of competitors to identify the magnitude of switching costs $\gamma_k(t)$.

### 5.5.1 Standard Deviation $\sigma_\varepsilon$

The standard deviation of payoff shocks $\sigma_\varepsilon$ can be identified from the final release dates of movies, $r_{T+1}$. When production shocks have zero variance ($\sigma_\varepsilon = 0$), studios play a perfect information game in which they compete for the most profitable release weeks. In this case, final release dates of studios should be concentrated around weeks that have the highest demand according to the function $R(r, \theta)$. For instance, suppose that some week $w^*_1$ has the highest expected flow of box office revenues, and $w^*_2$ is the second most profitable release week. If release timing decisions of studios were completely independent, we would expect studios to release all of their movies in week $w^*_1$; however, business stealing effect will prevent studios from releasing on the same week, and some of them will release in other weeks, e.g. $w^*_2$ and $w^*_3$. As a result, the final release dates should be mostly concentrated around these several weeks. By contrast, with high variance of production shocks ($\sigma_\varepsilon > 0$), release timing decisions of studios will appear random relative to the demand function $R(r, \theta)$. The most profitable weeks, such as $w^*_1$ or $w^*_2$, will often remain unoccupied because of unexpected production shocks experienced by the studios. Thus, the standard deviation $\sigma_\varepsilon$ is identified from the proportion of movies whose final release dates are concentrated around the most profitable release weeks.

### 5.5.2 Switching Costs $\gamma_k(t)$

Having estimated demand $R_k(r, \theta)$ and the standard deviation $\sigma_\varepsilon$, I can use the data on production delays to identify switching cost parameters $\gamma$. This part of the identification argument is similar to Section 4, with the difference that now I can use the demand function $R(r, \theta)$ to compute the expected revenues of studios under different configurations of release dates. This knowledge of counterfactual revenues allows me to recover the absolute values of switching costs, which was not possible in the reduced-form estimation. Specifically, when a movie delays and vacates a profitable release week, other studios may find it profitable to switch their release dates and capture the vacated slot. Moreover, from the shape of the demand function $R(r, \theta)$, we know exactly how much studios would gain from switching. If these gains from switching for some studio are relatively high, but it does not switch, we should conclude that this studio has relatively large switching costs $\gamma_k(t)$. Similarly, studios that readily reschedule their releases to capture even relatively small additional profits must have relatively low switching costs. Thus, the reaction of different studios to major production delays of competitors allows to identify switching costs of different studios, thus helping
to recover $\gamma_0$ and $\gamma_2$. Additionally, comparing delays that occurred early versus delays that occurred during the last stages of the game helps identify how fast switching costs increase over time, which allows us to recover the linear trend parameter $\gamma_1$.

5.6 Simulation Exercise

To confirm that the estimation procedure in Section 5.4 successfully recovers structural parameters, I estimate the model using simulated data. My goal is to recover parameters of the model using a dataset that mimics the real one. To this end, I generate data in which $K$ movies compete in $N = 200$ independent markets by choosing among $W = 5$ release weeks. The simulation exercise is repeated for $K = 2$, $K = 3$, and $K = 4$ to explore how performance of the estimator changes with the number of competitors. In simulated data, movies play the game of commitments that proceeds in $R = 12$ rounds, which can be interpreted as twelve months preceding the season of releases. I assume that each movie has either high switching costs $\gamma_{\text{high}} = 0.5$, or low switching costs $\gamma_{\text{low}} = 0.1$, where two values of costs are equally likely. All movies face the same uncertainty about their payoffs captured by random shocks $\varepsilon$ with standard deviation $\sigma_\varepsilon = 0.1$. Finally, qualities and week fixed-effects follow $q_k \sim U[0, 1]$ and $\alpha_w \sim U[-2, 0]$; demand parameters are set fixed at $\lambda = 0.5$ and $\pi = 0.5$; and the delay probability is $\mu = 0.005$.

Table A3 presents the estimates of parameters obtained from the simulated data. The true values of parameters are summarized in column 1, while column 2 reports the Maximum Likelihood estimates. To study whether bootstrap successfully recovers standard errors, I compare standard errors obtained from bootstrap with those computed using a Monte Carlo simulation. These two sets of standard errors are reported in columns 3 and 4. The results in Table A3 confirm that the estimator developed in Section 5.4 can indeed recover structural parameters of the model. All three coefficients are precisely estimated: standard errors appear small, and most of the estimates lie within 2-3 standard deviations from the truth. In addition, bootstrap standard errors have values close to those obtained from Monte Carlo simulation. In fact, the average absolute distance between two estimates is less than 15 percent, suggesting that bootstrap standard errors indeed provide a reasonable approximation to the true standard errors of parameter estimates.

6 Estimation Results

(Coming soon)
7 Concluding Remarks

(Coming soon)
References


Tables and Figures

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Table 1: **Summary statistics.** Panel A describes the data on pre-release announcements of studios for different movies, while Panel B reports descriptive statistics for revenues and observable movie characteristics including the budget, distributor, and number of theaters in which a movie was exhibited.
**Table 2:** The relationship between movie characteristics and the probability of switching.
The dependent variable is the indicator that a movie switches to a different release date in a given month. Robust standard errors in parentheses are clustered by movie. * p<0.05

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Movie rescheduled to the vacated slot?

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<th>(1.46)</th>
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<td>0.013</td>
<td>0.016*</td>
<td>0.020*</td>
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<tr>
<td>(7-8 months)</td>
<td>(1.63)</td>
<td>(1.65)</td>
<td>(2.01)</td>
<td>(2.45)</td>
</tr>
<tr>
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<td>(5-6 months)</td>
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<td>(1.98)</td>
<td>(1.46)</td>
<td>(0.87)</td>
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<td>0.003</td>
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<td>-0.002</td>
</tr>
<tr>
<td>(2-4 months)</td>
<td>(0.58)</td>
<td>(0.54)</td>
<td>(-0.15)</td>
<td>(-0.35)</td>
</tr>
<tr>
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<td>0.002</td>
<td>-0.001</td>
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<td>(&lt; 2 months)</td>
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<td>(-0.52)</td>
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<td>0.024*</td>
<td>0.041*</td>
<td>0.024*</td>
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<td>(7-8 months)</td>
<td>(16.76)</td>
<td>(6.71)</td>
<td>(3.70)</td>
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<tr>
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<td>(5-6 months)</td>
<td>(9.47)</td>
<td>(5.60)</td>
<td>(3.53)</td>
<td>(3.80)</td>
</tr>
<tr>
<td>MonthsToRelease</td>
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<td>0.037*</td>
<td>0.054*</td>
<td>0.035*</td>
</tr>
<tr>
<td>(2-4 months)</td>
<td>(16.13)</td>
<td>(9.11)</td>
<td>(4.80)</td>
<td>(5.60)</td>
</tr>
<tr>
<td>MonthsToRelease</td>
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<td>0.030*</td>
<td>0.045*</td>
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<td>(4.04)</td>
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Control variables

<table>
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<tr>
<td>MonthsToRelease</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Budget</td>
<td>Yes</td>
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<td></td>
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<tr>
<td>Distributor FE</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Genre FE</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age Rating FE</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Season FE</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Movie FE</td>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
</tbody>
</table>

| No. obs.              | 31,054 | 31,054 | 30,327 | 30,327 | 31,054 |
| R-squared              | 0.0045 | 0.0278 | 0.0304 | 0.0405 | 0.0011 |

Table 3: **Response of studios to major production delays of competing movies.** The table reports estimated coefficients and t-statistics (in parentheses). The number of observations fluctuates across specifications because of the missing data on production budgets of movies. * p<0.05
Appendix

A Proofs of Lemmas

(Coming soon)

B Numerical Example for the Simple Model

To illustrate how the equilibrium of the simple game depends on the switching costs $\gamma_1$ and $\gamma_2$, I solve the game using the concept of Subgame Perfect Nash Equilibrium. Because the game has a finite horizon, I can compute the unique equilibrium using backwards induction. The numerical example considered in this section assumes that qualities of movies are $\theta_1 = 1.5$ and $\theta_2 = 1.0$; market sizes are equal to $M_1 = 6.5$ and $M_2 = 5$; each movie delays with exogenous probability $\lambda = 0.1$; and supply-side shocks $\varepsilon_{ij}$ are normally distributed so that $\varepsilon_{ij} \sim N(0, \sigma^2_\varepsilon)$ iid across movies and weeks with $\sigma_\varepsilon = 0.5$. These numbers are somewhat arbitrary and are chosen to illustrate the main equilibrium forces rather than to generate realistic predictions.

The general property of the equilibrium is that the player with relatively high switching costs chooses to commit regardless of the order in which movies make decisions. For example, when $\gamma_1 = 5$ and $\gamma_2 = 0$, player 1 commits to release on week 1, whereas player 2 remains flexible regardless of the identity of the leader $L$. The roles are reversed when $\gamma_2 = 5$ and $\gamma_1 = 0$, in which case player 2 commits and player 1 remains flexible until the last period. Only when both switching costs are large, e.g., when $\gamma_1 = 5$ and $\gamma_2 = 5$, the commitment decisions depend on the exact sequence of moves. In this case, the player that moves first typically choses to commit, while its competitor remains flexible and waits to observe the realizations of shocks $\varepsilon_{ij}$ before choosing a release week.

The presence of commitments may have important effects on consumer surplus ($CS$). To illustrate, define consumer surplus as the number of consumers who watched a movie multiplied by the quality of that movie. For example, if movies 1 and 2 are released on weeks 1 and 2, consumer welfare from movie 1 is $M_1 \theta_1/(1 + \theta_1)$ and from movie 2 is $M_2 \theta_2/(1 + \theta_2)$. The total consumer surplus is a sum of these two values. The values of $CS$ for different combinations of $\gamma_1$ and $\gamma_2$ are presented in Figure A1.

Commitments may bring equilibrium further away or closer to the efficient sorting of movies across weeks. The efficient sorting arises when movie 1 is released on week 1, and movie 2 is released

$^{26}$In this model it never makes sense to commit to releasing on week 2 as it reduces the chance of capturing the high-demand market $M_1$ without generating any benefits.

34
Figure A1: **Equilibrium consumer surplus for different combinations of switching costs** $\gamma_1$ and $\gamma_2$. Consumer surplus from movie $i$ is defined as the number of consumers who watched it times the quality of this movie $\theta_i$. The graph plots the total consumer surplus from two movies for different combinations of switching costs $\gamma_1$ and $\gamma_2$.

on week 2; in this case, the allocation of movies across weeks maximizes the expected number of consumers who watch high-quality movie 1 (recall that qualities of movies are ordered, so that $\theta_1 > \theta_2$). In the numerical example above, increasing $\gamma_1$ helps movie 1 to capture the high-demand week 1, thus improving allocation efficiency and increasing consumer welfare. Intuitively, giving commitment power to movie 1 improves consumer surplus as it maximizes the number of consumers watching the high-quality movie. This effect explains why $CS$ increases when moving from point X to point Y in Figure A1. By contrast, consumer surplus is decreasing in $\gamma_2$ as commitments of movie 2 shift equilibrium away from the efficient allocation. Giving commitment power to movie 2 moves the equilibrium toward the point of inefficiency, in which most of consumers watch the low-quality movie 2; as a result, $CS$ decreases when moving from point X to point Z.

C Data on Production Delays

(Coming soon)
D Robustness Analyses

Figure A2: Reaction of studios to production delays of competing movies. The graph presents the estimated coefficients from Table A1 with 95% confidence intervals.
<table>
<thead>
<tr>
<th></th>
<th>Movie rescheduled to the vacated slot?</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RivalDelays_{t-6}$</td>
<td>0.005 0.006 0.004 0.002</td>
</tr>
<tr>
<td></td>
<td>(0.91) (1.04) (0.66) (0.37)</td>
</tr>
<tr>
<td>$RivalDelays_{t-5}$</td>
<td>0.000 0.001 -0.001 -0.001</td>
</tr>
<tr>
<td></td>
<td>(0.08) (0.23) (-0.17) (-0.22)</td>
</tr>
<tr>
<td>$RivalDelays_{t-4}$</td>
<td>-0.003 -0.003 -0.005 -0.003</td>
</tr>
<tr>
<td></td>
<td>(-0.55) (-0.55) (-0.98) (-0.57)</td>
</tr>
<tr>
<td>$RivalDelays_{t-3}$</td>
<td>0.005 0.004 0.002 0.006</td>
</tr>
<tr>
<td></td>
<td>(1.04) (0.86) (0.38) (1.17)</td>
</tr>
<tr>
<td>$RivalDelays_{t-2}$</td>
<td>0.008 0.008 0.006 0.008</td>
</tr>
<tr>
<td></td>
<td>(1.70) (1.70) (1.22) (1.68)</td>
</tr>
<tr>
<td>$RivalDelays_{t-1}$</td>
<td>0.011* 0.012* 0.009* 0.010*</td>
</tr>
<tr>
<td></td>
<td>(2.31) (2.48) (1.99) (2.15)</td>
</tr>
<tr>
<td>$RivalDelays_{t}$</td>
<td>0.014* 0.013* 0.010* 0.011*</td>
</tr>
<tr>
<td></td>
<td>(3.49) (3.34) (2.54) (2.76)</td>
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<tr>
<td>$RivalDelays_{t+1}$</td>
<td>0.004 0.004 0.001 0.000</td>
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<tr>
<td></td>
<td>(0.86) (0.93) (0.27) (0.05)</td>
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<tr>
<td>$RivalDelays_{t+2}$</td>
<td>0.004 0.002 -0.002 0.000</td>
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<tr>
<td></td>
<td>(0.89) (0.31) (-0.35) (-0.03)</td>
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<tr>
<td>$RivalDelays_{t+3}$</td>
<td>0.004 0.002 -0.003 0.000</td>
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<td>$RivalDelays_{t+4}$</td>
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<td>$RivalDelays_{t+6}$</td>
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<tr>
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<td>(-0.41) (-0.43) (-0.80) (-1.18)</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Budget</td>
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<td>Distributor FE</td>
<td>Yes</td>
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<tr>
<td>Genre FE</td>
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<td>Age Rating FE</td>
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<td>Season FE</td>
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Table A1: Response of studios to major production delays of competing movies. This table contains the results from the extended regression with the lagged values of the $RivalDelays$ variable. The table reports estimated coefficients and t-statistics (in parentheses). * p<0.05
<table>
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<td><em>RivalDelays</em> x</td>
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<tr>
<td>(7-8 months)</td>
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</tr>
<tr>
<td></td>
<td>(1.65)</td>
</tr>
<tr>
<td></td>
<td><em>RivalDelays</em> x</td>
</tr>
<tr>
<td>(5-6 months)</td>
<td>0.019*</td>
</tr>
<tr>
<td></td>
<td>(1.98)</td>
</tr>
<tr>
<td></td>
<td><em>RivalDelays</em> x</td>
</tr>
<tr>
<td>(2-4 months)</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
</tr>
<tr>
<td></td>
<td><em>RivalDelays</em> x</td>
</tr>
<tr>
<td>(&lt;2 months)</td>
<td>0.002</td>
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<tr>
<td></td>
<td>(0.25)</td>
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<tr>
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<td><em>MonthsToRelease</em></td>
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<tr>
<td>(7-8 months)</td>
<td>0.024*</td>
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<tr>
<td></td>
<td>(6.71)</td>
</tr>
<tr>
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<td><em>MonthsToRelease</em></td>
</tr>
<tr>
<td>(5-6 months)</td>
<td>0.023*</td>
</tr>
<tr>
<td></td>
<td>(5.60)</td>
</tr>
<tr>
<td></td>
<td><em>MonthsToRelease</em></td>
</tr>
<tr>
<td>(2-4 months)</td>
<td>0.037*</td>
</tr>
<tr>
<td></td>
<td>(9.11)</td>
</tr>
<tr>
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<td><em>MonthsToRelease</em></td>
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<tr>
<td>(&lt;2 months)</td>
<td>0.030*</td>
</tr>
<tr>
<td></td>
<td>(7.03)</td>
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</tbody>
</table>

|                                | Vacated week is a holiday?     |
|                                |                                |
| President’s Day                | 0.012                          |
|                                | (1.97)                         |
| Memorial Day                   | -0.008                         |
|                                | (-1.09)                        |
| Independence Day               | 0.005                          |
|                                | (0.91)                         |
| Thanksgiving                   | -0.010                         |
|                                | (-1.08)                        |
| Christmas                      | 0.011*                         |
|                                | (2.03)                         |
| New Year                       | 0.014*                         |
|                                | (4.92)                         |

|                                | Control variables              |
|                                |                                |
| Budget                         | Yes                            |
| Distributor FE                 | Yes                            |
| Genre FE                       | Yes                            |
| Age Rating FE                  | Yes                            |
|                                |                                |
| No. obs.                       | 30,327                         |
| R-squared                      | 0.0304                         |

Table A2: Response of studios to major production delays of competing movies. This table contains the results from the extended regression that controls for the profitability of the vacated slot. The table reports estimated coefficients and t-statistics (in parentheses). * p<0.05
### E Simulation Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Truth</th>
<th>Estimates</th>
<th>Standard Errors Monte Carlo</th>
<th>Standard Errors Bootstrap</th>
</tr>
</thead>
<tbody>
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<td><strong>Two movies (K = 2)</strong></td>
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<td></td>
</tr>
<tr>
<td>(\gamma_{\text{high}})</td>
<td>0.500</td>
<td>0.500</td>
<td>0.024</td>
<td>0.031</td>
</tr>
<tr>
<td>(\gamma_{\text{low}})</td>
<td>0.100</td>
<td>0.103</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>(\sigma_\varepsilon)</td>
<td>0.100</td>
<td>0.111</td>
<td>0.006</td>
<td>0.007</td>
</tr>
<tr>
<td><strong>Three movies (K = 3)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\gamma_{\text{high}})</td>
<td>0.500</td>
<td>0.512</td>
<td>0.018</td>
<td>0.018</td>
</tr>
<tr>
<td>(\gamma_{\text{low}})</td>
<td>0.100</td>
<td>0.109</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>(\sigma_\varepsilon)</td>
<td>0.100</td>
<td>0.115</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td><strong>Four movies (K = 4)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\gamma_{\text{high}})</td>
<td>0.500</td>
<td>0.508</td>
<td>0.012</td>
<td>0.010</td>
</tr>
<tr>
<td>(\gamma_{\text{low}})</td>
<td>0.100</td>
<td>0.107</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>(\sigma_\varepsilon)</td>
<td>0.100</td>
<td>0.113</td>
<td>0.003</td>
<td>0.002</td>
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</tbody>
</table>

Table A3: **Parameter Estimates from the Simulation Exercise.** The first column reports the true values of parameters used to generate data, while the second column presents parameter estimates. In the third and fourth column, I compare standard errors of estimates obtained from bootstrap and Monte Carlo simulations. The simulated sample includes \(N = 200\) markets, \(W = 5\) release weeks, and \(R = 12\) rounds of announcements.