Competitive Dynamics in the Release Date Pre-announcements of Motion Pictures

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Abstract

Release timing is widely recognized as a critical determinant of motion picture box office revenues. It is also one of the most critical competitive tools used by the studios in the motion picture industry. To facilitate the release date selection, studios decide and pre-announce the targeted release dates on a weekly basis long before the actual release of their forthcoming movies. Their choices of release dates and then subsequent changes in these during the pre-announcement period are highly strategic in nature. We examine these strategic interactions in this research.

In particular, we examine the following few aspects of the strategic interactions. They span over *multiple* decision or pre-announcement periods. In every period, studios make *simultaneous* decisions on whether to pre-announce and which weekend to target. More importantly, these decisions are essentially *discrete* in nature; this is in contrast with the more traditional choices of continuous price or advertising levels. When making these simultaneous decisions, studios might also conjecture their competitors' decisions and account for the *inter-temporal* effects of these current actions on the future competition; that is, competitive dynamics may play an important role in the studios' release date decisions.

Given these features of the release date pre-announcement game, traditional tools used to study competitive interactions are not appropriate in this context. Therefore, we apply the Markov Perfect Nash Equilibrium (MPNE) framework developed in industrial organization to capture the key features, particularly the competitive dynamics, of the game and forecast the competitive responses to pre-announced release date decisions. We apply a newly developed methodology to empirically estimate the proposed dynamic model using historical data of pre-announced release dates from the U.S. motion picture industry. We further compare the proposed dynamic model with the conventionally used static model and myopic model in the literature.

Our results demonstrate that studios are forward-looking and maximize the inter-temporal expected payoffs during decision making; ignoring such critical competitive dynamics produces inaccurate inferences on studios' decision processes and strategic interactions; accounting for the competitive dynamics increases a studio's predictive power of competitor decisions and responses to pre-announced release date decisions. Therefore, our study can help improve the studio's managerial decision making of the release timing and hence the potential revenues. The analytical framework and methodology can be generalized to study other interesting marketing problems in various industries, such as books and music releases, TV programming, and so on.

Key words: Discrete Dynamic Game, Markov Prefect Nash Equilibrium, New Product Pre-announcement, Market Entry and Exit, Motion Picture Industry, Release Timing.

1. INTRODUCTION

An important issue in understanding competition in a market is understanding how firms' choices define their competitive set and hence their profitability. That is, firms are not assigned competitive sets exogenously, but choose via their own actions with whom they compete directly, and which competitors are less important. Their choices, reflected in their locations in the competitive space with varied intrinsic attractiveness and varied competitive intensity, determine how profitable they are. In this research, we examine the issue of how firms choose their competitive sets or locations in the context of the U.S. motion picture industry where frequent competitive entry and exit may induce strong competitive dynamics; that is, these dynamics are mainly driven by the supply-side strategic choices that alter the competitive sets from one period to another. Specifically, we are interested in studying how various studios choose the release timing of their movies within a specific season prior to the actual releases of these movies.

Given the limited supply of attractive release dates or "locations" in the competitive space, competition among studios for attractive release dates is intense, and is one of the most critical competitive choices a studio can make. Studios often pre-announce the targeted release dates long before the actual releases of their movies; they may further adjust these announced dates when other competitor movies change their targeted release dates, new competitors appear into the release schedule, and currently scheduled movies exit into other release seasons. Therefore, the competitive set for any movie evolves over the course of the pre-announcement period into the final release schedule. Indeed, as an industry expert told us:

> *"Studio executives look at these (release schedules) as a giant entertainment chess game" - Manager, Exhibitor Relations Inc.*

Since studios' profitability can be greatly influenced by the release timing of their movies, a complete understanding of how studios decide and adjust the targeted release dates during the pre-announcement period will lead to the improved managerial decision making of the release timing and therefore the box office revenues. In this research, we intend to capture the structure of the release data pre-announcement game and in particular study the role of the competitive dynamics in the inference of studio managers' decision processes and strategic interaction and in the forecast of the competitors' strategic responses to the pre-announced release dates.

However, modeling such a game of release date pre-announcements is a complicated task due to the following reasons: (i) the game is played over *multiple* decision or pre-announcement periods; (ii) in every period, studios make *simultaneous* decisions on whether to pre-announce, which weekend to target within one specific season defined as several weeks centering around a holiday weekend such as the Memorial weekend, and whether to exit a specific season; (iii) more importantly, all these decisions are *discrete*; this is in contrast with the more traditional choices of continuous price or advertising levels; and (iv) most importantly, when making these simultaneous decisions, studios might conjecture their competitors' decisions and further account for the *inter-temporal* effects of these current actions on the future competitive set and hence expected future payoffs; that is, competitive dynamics may play an important role in the studios' release date decisions.

Given the above features of the release date pre-announcement game, traditional tools used to study competitive interactions are not appropriate for our context. Therefore, we apply the Markov Perfect Nash Equilibrium (MPNE) framework developed in industrial organization to capture these key features of the game and to forecast competitive release date decisions. We apply a newly developed methodology (Aguirregabiria and Mira 2002) to empirically estimate the model using historical data of pre-announced release dates from the U.S. motion picture industry. We further compare the proposed dynamic model with the conventionally used static model and myopic model in the literature.

Our analysis yields the following three key findings. (i) Studios are forward-looking and maximize the inter-temporal expected payoffs during decision making. Specifically, while accounting for the potential switching costs, studios tradeoff the anticipated demand or the intrinsic attractiveness of a specific weekend with the competition from competitor movies, particularly those of the same genre, targeting the same weekend; they further account for the inter-temporal effects of their current actions on the composition of future competitive sets and therefore future expected payoffs. (ii) Ignoring such critical competitive dynamics produces inaccurate inferences on studios' decision processes and strategic interactions. In particular, the static model analyzing only the final release dates overstates the anticipated demand, understates the competitive intensity, and further understates the anticipated demand gap between the holiday and non-holiday weekends. (iii) Accounting for such competitive dynamics increases a studio's predictive power of competitor decisions and responses to pre-announced release date decisions. Therefore, our analysis can be incorporated into a decision support system to either automate a manager's release date decisions or serve as a decision guide to help the manager avoid over-reaction to competitor moves and therefore avoid unnecessary switching costs. These improved release date decisions should translate to the improved studio revenues.

The rest of this paper is organized as follows. In section 2, we review relevant literature. In section 3 and 4 respectively, we document industry evidence in support of studying this problem, and provide data details. We present the models and estimation methods in section 5, and discuss the empirical results in section 6. We conclude in section 7.

2. RELEVANT LITERATURE

This research complements, and builds on, prior work in both the substantive and methodological areas. There are two substantive areas related to our work – the modeling of the motion picture industry, and the literature of new product pre-announcements. Methodologically, our work is related to the studies of dynamic competition. We discuss these sequentially.

There is a rich stream of literature in marketing on modeling the motion picture industry. One stream has focused on modeling the determinants of movie performance. A majority of these studies focus on modeling demand for movies. For example, Zufryden (1996) measures the impact of advertising on movie revenues by modeling how awareness is generated and translates to intention and finally to the purchase of a movie ticket. Sawhney and Eliashberg (1996) model in greater detail how intention translates to purchase by modeling when the decision is made and when it is acted on. Neelamegham and Chintagunta (1999) model the impact of the number of screens, distribution strategy, and movie attributes on weekly demand. Einav (2002 working paper) uses a discrete choice model to decompose and separately identify the effects of intrinsic movie qualities and the effects of underlying demand in the observed seasonality of industry sales or box office revenues. Another series of studies have focused on modeling the determinants of total revenues of movies. Among the variables studied are stars (Sawhney and Eliashberg 1996), genre (Jedidi, Krider, and Weinberg 1998), advertising levels (Zufryden 2000), critical reviews (Eliashberg and Shugan 1997), etc.

From our perspective, the above literature has at least two important but understudied areas. The first is that the role of competition in the performance of a movie has not been modeled in a structural framework. Consider, Litman and Ahn (1998) who use the reduced-form measure of concentration ratio to understand the impact of "neighboring" movies on the performance of any movie. Jedidi, Krider, and Weinberg (1998) and Zufryden (2000) have a count measure of movies released in the same week as a proxy for competitive effects. Ainslie, Drèze, and Zufryden (2002 working paper) use a sliding-window logit model to capture the effects of competition or the number of competitors screened in the same week on the movies' box office performance. An issue with using concentration ratios, count measures, or similar measures is that these measures are not exogenous, but rather result from a competitive game played in this industry even before the actual release of these movies and are hence endogenous. Modeling this game can provide richer insights into competition in the industry and is one of the goals of this paper.

Another understudied area in movie research is the role of pre-announcements of movie release dates. That is, studies in this literature have focused on what happens after a movie is released and not on how the release schedule results from a game that precedes the actual release. There are two important exceptions in this literature. Krider and Weinberg (1998) theoretically model the timing game between two movies that compete for the similar audience. They model the actual release dates in a framework of a one-shot game instead of a repeated game that starts with the earliest pre-announcements and ends with the final release schedule as in our context. The other important exception is the empirical analysis by Einav (2003 working paper) who studies the sequential instead of simultaneous choices of release dates. He limits the analysis to 3 competitive movies per season during the pre-announcement process for the computational tractability. In our study, we model the complete sequence of the simultaneous-move pre-announcement game for as many as the top 20 movies targeting each season in order to capture more completely the nature and the richness of the competitive game in this industry.

In addition to the above literature on the pre-announcements in the movie release dates, there is of course, a much larger and richer literature in marketing on pre-announcements in general[1]. Various authors have demonstrated how early announcements are competitively pre-emptive (Smiley 1988; Bayus, Jain and Rao 2001). Others have demonstrated how pre-announcements can help generate demand via word-of-mouth and other effects (Eliashberg and Robertson, 1988). Yet others have recognized that pre-announcements affect both demand and supply (Robertson, Eliashberg, and Rymon 1995; Manceau, Eliashberg, and Rao 2002 working paper). Our paper adds to this stream of literature by empirically modeling the entire sequence of pre-announcements by competitor studios while also modeling how these competitors can potentially account for the revenue implications of their pre-announcements in the presence of competitive entry and exit. To the best of our knowledge, this is one of the first such attempts at this problem.

Finally, another understudied area in the movie research area, and in the study of competition in general, is the study of competitive dynamics. As Elberse and Eliashberg (2003) point out, there is a serious "shortcoming(s) in the literature addressing the drivers of motion picture performance: a prevalence of static approaches…". The focus of their work is on the dynamics between the number of screens and revenues and their co-evolution over time during international diffusion of the movies. Instead of focusing on the dynamics after the actual releases of movies, our paper focuses on the dynamics of release date decisions prior to the actual release. Additionally, our work is grounded more in the expected payoff maximizing explanations of the competitive interactions.

While the study of competitive dynamics might be limited in the movie context, there is a large literature in marketing in this area, specifically in the area of differential games (Case 1979; Erickson 1992; Chintagunta and Vilcassim 1992; Chintagunta and Rao 1996). This area of research has focused on how demand-driven dynamics (e.g., the

[1] "Pre-announcements" is a commonly used terminology in the marketing literature meaning the announcements *prior to* the actual release of the new products. We may use "announcements" interchangeably in the later text.

accumulation of advertising goodwill, or preferences for brands evolving over time) result in supply dynamics. While there are important demand-driven dynamics in the movie industry (e.g., word of mouth effects), this is not the focus of our paper. Instead we focus on supply side dynamics, that is, how studios try to maximize the possible opening-weekend success of their movies by dynamically interacting with one another in the selection of optimal release dates prior to the actual release of these movies. This focus on the first week or opening weekend revenues minimizes the impact of demand dynamics by not examining the later weeks, as well as the dynamics between movie and video release, or the international movie release schedule dynamics.

To model supply side competitive dynamics, the most promising conceptual framework is that of Markov Perfect Nash Equilibria (MPNE hereafter; Maskin and Tirole 1988a, 1988b). This framework is similar to the closed-loop no-memory equilibrium (Basar and Olsder 1982; Starr and Ho 1969). The estimation procedure involves estimating the transition matrix from one period to the next, as well as estimating the value function for each player as it moves through this transition matrix. In this framework dynamics result from players' strategies being functions of each other's in a finite or infinite horizon payoff or expected payoff maximization problem. Hence, this might provide a better fit for the pre-announcement game in the movie industry.

So far, this framework has been used mainly in economics (Pakes and McGuire 1994, 2000; Erickson and Pakes 1995, etc.) and to the best of our knowledge in only one marketing paper (Chan and Seetharaman 2003 working paper) for dynamic games with *continuous* choices (for detailed estimation procedures for continuous choice dynamic games, please refer to Berry and Pakes 2000 working paper). Several exciting developments in this area enable the application of this framework to *discrete* games (note that in our context the choice of release dates is a choice of whether to pre-announce a release date (entry), whether to target a different season (exit), and which weekend to target within a specific season; and is hence a discrete choice; more on this in the forthcoming sections). Specifically, Pakes and Berry (2002 working paper) provide a set of assumptions under which there is only one set of equilibrium policies that are consistent with the data. They develop an estimation procedure that alleviates the computational burden for discrete dynamic games. In our analysis, we apply an alternative estimation method developed by Aguirregabiria and Mira (2002 and 2003 working paper) that we will elaborate in section 5.

To summarize, we apply the MPNE framework to analyze how studios make the release date decisions or pre-announcements prior to the actual releases of their movies in the U.S. motion picture industry. We focus on the role of the competitive dynamics in this game induced by studios' choices of release dates therefore the competitive sets in the presence of frequent competitive entry and exit. In particular, we seek to address the following research questions.

First, do studio managers account for the competitive dynamics in the competitive set composition while selecting the release dates?

Second, will our inference about the release date decisions and strategic interactions among studios differ if we ignore the competitive dynamics?

Third, can accounting for the competitive dynamics improve a studio manager's prediction of competitors' decisions or responses to the pre-announced release dates?

3. INDUSTRY BACKGROUND

The U.S. motion picture industry is a multi-billion dollar industry and has been steadily growing in the past few decades. Table 1 has listed the major industry statistics.

------------------- Table 1 ----------------------

Currently (as illustrated in Figure 1), major studios (who resemble the "manufacturers"), such as MGM, Sony, Paramount, and Universal, integrate the production and distribution of movies[2]. Exhibitors (who resemble the "retailers") own the theaters and display the movies to the moviegoers (or the "consumers").

------------------- Figure 1 ----------------------

3.1. Why is release timing critical

[2] There also exist a number of small independent producers who use either independent distributors or the major studios' distribution channels. We later focus our data analysis on the top 20 movies per season measured by production costs that are predominantly (87.4% of them) distributed by major studios.

As mentioned briefly in the introduction, release timing of motion pictures is a critical determinant of the studios' box office revenues. Unlike several other commonly studied industries, the motion picture industry features uniform pricing for differentiated products or movies in all first-run theaters in a season. Therefore, studios mainly compete on non-monetary features such as release timing[3].

Release timing is very critical in the motion picture industry also for the following reasons. First, there is significant seasonality in the observed ticket sales or revenues in this industry (see Figure 2). Major holidays such as President's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving – Christmas – New Year Day and the few weeks surrounding them, represent the majority of the annual box office income by major studios[4]. This observed seasonality is partially due to the fact that movies are essentially experience goods and consumers need to allocate time to go to theaters; therefore, holiday weekends typically represent a higher intrinsic or underlying demand for movies[5]. Second, profitability is clearly also a function of the competitor movies released around the same time. Studios select the competitive set for their movies through the release timing decisions. Third, the importance of the release dates is further magnified by the short product life cycle of the movies. Figure 3 illustrates the exponential decay in box office revenues for a typical movie in this industry[6]. The opening weekends typically account for almost 40% and the first 4 weeks account for almost 80% of the total box office revenues. The high revenues in the opening weekends further create the word of

[3] There does appear to be some quantity competition in this industry. Specifically, movie studios decide how "wide" the release will be, e.g., whether to start with a few major cities and then expand to the nationwide release in a few weeks. We do not account for this quantity competition for various reasons. First, we do not have complete data on release widths for all movies. Second, it appears from the data that most "major" or high-budget movies (81% of the top 20 movies per season in our selected data sample) are released nationwide right away. In our empirical study, we only analyze the pre-announced *nationwide* release dates. In future research, modeling the width variable would be a useful extension if reliable data could be obtained.

[4] "In the beginning, there was no such thing as a 'holiday movie season'", said Jeanine Basinger, chairwoman of the film studies department at Wesleyan University, "you just release movies". The turning point came with two 1970's summer films, "Jaws" and "Star Wars", and then the notion of a movie season was born. Soon, studios were jockeying over the most lucrative opening weekends, which usually mean the prime summer weekends that collectively account for about 40% of the annual box office revenues in the U.S. motion picture industry.

[5] Einav (2002 working paper) shows how to separately identify the two major driving forces of the observed seasonality in industry ticket sales and revenues: (i) the true underlying consumer demand for movies; and (ii) the studios' endogenous choices of release timing.

[6] Of course, there exist some variations in the decay patterns among movies; however, "sleeper movies" that start off with mediocre box office performance and later attract more audience are rare.

mouth effects critical for the box office performance of the movie in the subsequent weeks. Indeed, the opening weekend box office revenues are widely taken by this industry as the best predictor of the overall success throughout a movie's theatrical run, and even international releases and the video/DVD sales. Finally, the revenue-sharing schemes between the studios and the exhibitors make the opening weekends most critical for studios. Specifically, studios obtain in the first week the highest percentage (typically 70 ~ 90%) of the box office revenue after deducting the exhibitors' costs; and this percentage reduces quickly over the subsequent weeks.

------------- Figure 2 -----------------

------------- Figure 3 -----------------

Due to the above reasons, studio managers judiciously choose the opening weekends for their forthcoming movies. In doing so, pre-announcing the targeted release dates prior to the actual releases is clearly an important device and an effective coordinating mechanism among studios to configure the release schedules.

3.2. The release date pre-announcement game

Based on our conversation with several industry insiders, studios make and pre-announce the release date decisions on a weekly basis. Then these decisions will be sent to industry research firms such as Exhibitor Relations Inc. (ERI thereafter). ERI has been organizing and publishing these studios' pre-announced release date decisions every week since 1974 (even though the industry has a much longer history of pre-announcing targeted release dates). The main audience of these publications includes various studios, exhibitors, advertising agencies, merchandisers who produce and distribute movie-related toys, and other relevant businesses[7].

Studios pre-announce the targeted release dates for their forthcoming movies up to two years prior to the actual releases (see Figure 4 for the timeline of the major industry activities), and further alter the previously announced release dates till as late as

[7] These publications mainly target business instead of consumer audience. Studios typically announce the specific release date decisions to the consumer audience one to two months prior to the actual release of their movies; therefore consumers play a minimum role in this pre-announcement game (though we recognize that the Internet has very recently enabled some movie-goers to acquire information on specific release dates of forthcoming movies much earlier on).

a few weeks prior to the actual release dates. They alter the targeted release dates as new movies enter the pre-announcement game and the existing rivals adjust their release weekends within the same season or exit the season by targeting a different one. Most of the changes in the previously announced release dates are within the range of a few weeks; this further indicates that most of these changes are for strategic reasons instead of other reasons such as production delays[8].

------------- Figure 4 ------------------

Studio managers indicate that they play the game very seriously and call this game "a good-faith coordination" among studios for many years. They make and announce the release date decisions that represent serious commitments and therefore are not "cheap talk" commonly defined as *costless, unverifiable, and non-binding statements* (Farrell 1987). This is especially true given the substantial costs of changing the previously announced release dates in this industry. These costs potentially include the interest payment associated with the production costs, costs of changing the advertising messages and campaign schedules, costs of changing the deadlines for film editing and delivery to theaters, and other costs such as the reputation costs among competitor studios, exhibitors, merchandisers, and even consumers[9].

Table 2 illustrates a simple example of a pre-announcement game among three comedies, *Legally Blond* by MGM/UA, *America's Sweethearts* by Sony, and *Cats and Dogs* by Warner Brothers, all released into the weeks around the Independence Day of 2001. Since 3/15/01 when *Cats & Dogs* announced to target the Independence Day, it has been a direct competitor with *America's Sweethearts* that targeted the same opening weekend. On 4/15/01, *America's Sweethearts* decided to switch away from *Cats and*

[8] The rule of thumb to detect such production related reasons is that the release dates were pushed back to a "vague" date or pushed back for a relatively long time such as a few months. Other minor reasons to alter the previously announced release dates include occasional changes in social and political environments and sometimes changes in advertising scheduling (which, if occur, may only occur towards the very end of the pre-announcement game since almost all advertising campaigns in this industry start about two months prior to the actual releases of the movies).

[9] In addition, if cheap talk were dominant, we would anticipate seeing a "war of attrition". That is, studios "plant their flags" early on in order to pre-occupy the hot holiday weekends, hoping that other competitors would be scared away. However, our data analysis has shown that movies are not only shifted "away" but also shifted "into" attractive holiday weekends later on during the games.

Dogs and pushed back the release date by about one week to 7/13/01. Unfortunately for *America's Sweethearts, Legally Blond,* which only announced vague release timing such as "year 01" or "summer 01" at the early stage of the game, announced the same release date. Two weeks later, *America's Sweethearts* pushed back the date again by one week to 7/20/01 to avoid competition with *Legally Blond*. This example illustrates how studios announce and fine-tune the targeted release dates before they locate their movies into the "best spots" as new competitors enter the game and old competitors change their release dates or target a different season.

------------- Table 2 ------------------

4. DATA DESCRIPTION

4.1 General data description

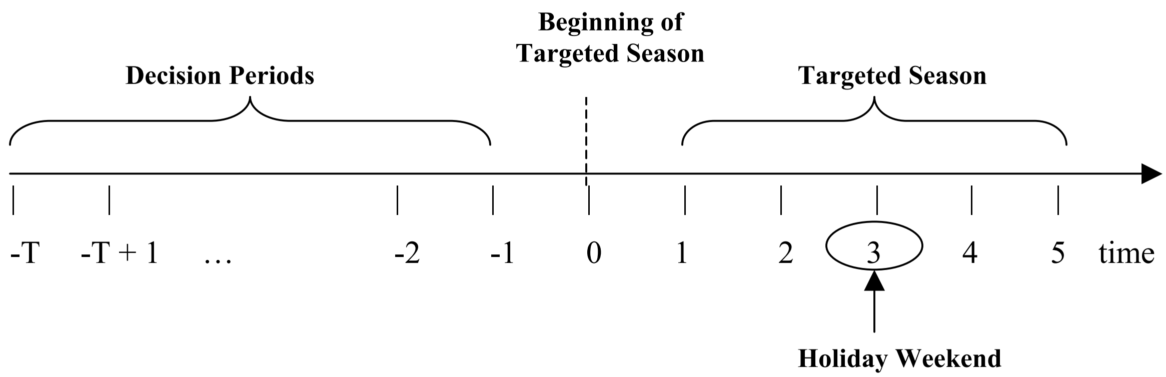
We obtained the historical box office data from A.C. Nielsen EDI (thereafter EDI) and the pre-announcement data from ERI.

The EDI box office data set has movie titles, distributor/studios, domestic release dates, the number of screening theaters over the first 10 weeks' run since release, run time, directors, screenplay, cast, estimated negative costs (production costs), genre, and the box office revenue for the first 10 weeks and the first 10 weekends since release for the 4186 movies released in the U. S. between 1984 and spring 2002.

The pre-announcement data contain major studios' bi-weekly decisions and pre-announcements of targeted release dates for most movies released in the U. S. between 1990 and spring 2002[10]. We matched 2560 titles between the box office and the pre-announcements data sets.

4.2 Game structure and the data selection

[10] ERI also publishes weekly interim reports but only made the official bi-weekly reports available to us.



As we mentioned earlier, there are several "hot" holiday weekends and surrounding weekends for which all studios are vying. As illustrated in the above graph, a "season" is defined as two weeks before and two weeks after centering around a holiday weekend. This definition is consistent with the industry practice and with the literature (Einav 2003 working paper). Most of the strategic actions are taken targeting these few holiday seasons, such as President's Day season, Memorial Day season, Independence Day season, and Labor Day season included in our data analysis[11].

A "game" is defined as the strategic interactions or a sequence of pre-announced release dates targeting one specific season. We identified 46 such games from our data. A randomly selected set of 40 games is used for model calibration and the other 6 for prediction exercises.

These games have from 6 to 43 (bi-weekly) decision periods, such as 1/15, 1/30, 2/1, each of which are essentially the dates of the ERI publications of the pre-announced release dates by all major studios. The beginning (period) of a game is defined as when at least two movies announced specific nationwide release dates. And the game ends at the last decision period right before the beginning of the targeted season.

In each game, the "players" are defined as the top 20 movies measured by their production costs[12]. These 20 players, we believe, can well capture the nature of the

[11] We excluded the Thanksgiving season and Christmas - New Year season mainly because we observed in our data frequent switches across these two seasons. Therefore, it is unclear whether the decision processes and the strategic interactions in these two seasons are consistent with those in the other four seasons we have selected for analysis where cross-season switches are rare.

[12] This is reasonable in the sense that studios often use the estimated production costs as a proxy to distinguish major competitors from the fringe ones during the pre-announcement period prior to the actual releases of their movies. We selected these 20 movies from all movies that at some time point announced to target this season.

strategic interactions of each game[13]. We further distinguish "incumbents" vs. "potential entrants". For each decision period, "incumbents" are defined as those who have previously announced specific release dates and "potential entrants" as those who may announce in the future but have not done so by the current decision period.

The incumbents' choice set includes the 5 possible weekends[14] within the targeted season and an "exit" option, that is, to target any other weekends outside of the season. Besides these 6 choice alternatives, potential entrants have an additional alternative of "no entry", that is, not to pre-announce any specific targeted release dates.

We focus our analysis on only the specific nationwide release dates announced and classify the "vague announcements" such as "summer 2001" or "fourth quarter 2001" into either a "no entry" option for the entrants or an "exit" option for the incumbents. This is because (i) a vague announcement does not contain enough information for us as researchers to model the attractiveness of a particular release date; (ii) a vague announcement may not contain enough information for competitor studios to determine their strategic responses; and (iii) a vague announcement can reflect production uncertainty and might not be strategic at all. Also note that if a movie announced in the prior period(s) but not in the current period, we impute the data for the current period with the most recent specific release date announcement.

4.3 Descriptive statistics of the selected data sample

The mean length or mean number of decision periods of the 46 games is 16.46 with the standard deviation of 1.28. Among the 920 movies selected in the 46 games, about 87.4% are from major studios such as Disney and Sony (Table 3)

------------- Table 3 ------------------

[13] More than three quarters of the total box office revenue come from the top 20 movies for these seasons. The number of players for each game is fixed and assumed to be exogenous and known to all players. This is a reasonable assumption given the fact that the number of movies released annually has been fairly stable during the past 10 years or so (see Table 1). In addition, each movie is assumed to be an independent player even though some may be distributed by the same studio. We hope to account for the effects of studios' portfolio or product line management on the release date selections in future research.

[14] We focus on the "weekends" mainly because the majority (about 80%) of the movies are released over Fridays and the majority (about 80%)of the weekly box office revenues are from the weekends. Therefore all pre-announcements targeting Tuesday up to Monday of the following week are grouped into the same (Friday) opening weekend.

Figure 5 illustrates the distribution of these movies in our data sample by the timing of initial pre-announcements of targeted release dates. Based on our definition of the beginning of the game, the mean number of months between the time of initial pre-announcements and the initial pre-announced release dates is 5.81 months (standard deviation 2.65, minimum 0.5, and maximum 19 months). The mean number of months between the time of initial pre-announcements and the actual release dates is 7.74 months (standard deviation 4.17, minimum .2, and maximum 38.3 months).

-------------- Figure 5 ------------------

About 79% of the selected 920 movies switched their announced release dates at least once (Figure 6).

-------------- Figure 6 ------------------

Figure 7 further illustrates the magnitude of the period-to-period changes in the pre-announcements, which is defined as the differences in weeks of the currently announced release dates relative to the most recently announced release dates. As we can see from Figure 7, 84% of the pre-announcements represent no changes from the most recently announced release dates. In addition, the majority of these differences are within the range of a few weeks; this, as we mentioned earlier, signals that most of the changes in the targeted release dates are for competitive reasons instead of for production delays. In addition, these switches are fairly symmetric (with more movies understandably push back than push up the release dates).

-------------- Figure 7 ------------------

5. MODELING AND ESTIMATION METHODS

5.1 The conceptual framework of our model

As we mentioned in the previous sections, the pre-announcement game played by the studios is a discrete time dynamic game with discrete choices. We apply the Markov

Perfect Nash Equilibrium (MPNE) framework (Maskin and Tirole 1988a and 1988b; Ericson and Pakes 1995) to capture the decision processes and strategic interactions among studios in this dynamic game. The dynamic Nash Equilibrium is realized in a given state space when decisions made by all players (defined in a probability structure for our context) based on conjectures of their competitors' decisions rationalize or match these conjectures (again, in a probability structure).

A "state" in the state space is defined as all the information a player has by the current time period, or in our context, the competitor movies targeting each of the alternative weeks. Given a specific state, each manager makes the decision by estimating and comparing the attractiveness or values among alternative weekends. These values rely on the manager's conjectures of the competitors' actions that determine the competitive state the manager potentially faces. These value functions form the basis of the estimated choice probabilities for each alternative weekend. These probabilities form the basis of a likelihood function from which the maximum likelihood estimates of the parameters are obtained.

5.2 The value function and the Bellman Equation

Below are some useful notations:

i, j = movies or players of the game = 1, 2, …, N;

$N = 20$ = total number of movies or players per game;

w = alternative weekends; ($w = 0$ stands for no entry or no pre-announcement yet; $w = 1 \sim 5$ stand for one of the 5 weekends within the targeted season, in which $w = 3$ stands for the holiday weekend and $w = 1, 2, 4, 5$ stand for the non-holiday weekends; $w = 6$ stands for the "exit" option or all the other weekends outside of the targeted season)[15];

g = game = 1, 2, …, G;

$G = 46$ = total number of games or repeated samples in the data;

t = finite and discrete decision periods of the game = 1, 2, …, T_g;

n_w = number of competitor movies targeting weekend w;

[15] For simplicity, we call these choice alternatives "alternative weekends" in the later text.

$\theta = [\alpha, \beta, \gamma]' =$ various parameters in the model capturing the effects of anticipated demand, competition, and switching;

δ = discount factor and $0 < \delta < 1$[16];

$a_{iE} \in A_E$ where $\mathrm{A_E} =$ weekends $0,1,...,5,$ and 6 = action space for the potential entrants;

$a_{iI} \in A_I$ where $\mathrm{A_I} =$ weekends $1,2,...,5,$ and 6 = action space for the incumbents.

As we mentioned in section 5.1, we use the value function to capture the attractiveness or the expected payoff of each alternative "weekend". A studio manager's objective is to select one weekend that has the highest value among several alternative weekends.

This value function is a discounted sum of the values for this alternative weekend in each decision period over the entire game or decision horizon. This discounted sum of values is concisely captured by the Bellman Equation commonly used in the literature of dynamic optimal control that simply consists of two components – the expected payoff for the current period and the discounted expected payoff for the future period (please refer to Appendix A1 for further details of the derivation of the Bellman Equation). We introduce the expected payoff function for the current period first.

In our research context, we include the following variables that may affect the expected payoff for the current period: (i) the anticipated or perceived underlying consumer demand for movies in each alternative weekend from the studio managers' perspectives[17]; (ii) the competition from competitor movies; and (iii) the effects of switching.

[16] In the literature, this discount factor is typically fixed at a value between 0.9 and 0.99. We have tried various values of this discount factor to ensure robustness of the results.

[17] We estimate the anticipated or perceived underlying demand using the pre-announced release date decisions under the assumption that studio managers make the optimal decisions given "their" anticipated or perceived demand; however, such "anticipated or perceived" demand by managers may not perfectly match the "true" underlying consumer demand for movies. In future research, we intend to further incorporate the demand-side analysis of the box office revenues to detect the gap between the anticipated/perceived demand and the true demand, therefore improve the managerial decision making on release dates by offering easy-to-use rules on how to bridge the gap.

The reduced-form representation of the expected payoff or revenue for movie i if it were released in weekend w is[18] (for simplicity, we drop the notations of game g and decision period t since the equations in the forthcoming text apply for each decision period in each game):

(1) $$E\pi_{iw}(s) = \alpha_w D_w + \beta_{sg} n_{iw\_sg} + \beta_{dg} n_{iw\_dg} + \gamma I_{switch}$$

where $\alpha_w D_w = \alpha_{no\_entry} D_{no\_entry} + \alpha_{non-holiday} D_{non-holiday} + \alpha_{holiday} D_{holiday}$.

This equation applies to both potential entrants and incumbents with the only difference that they have different choice sets. That is, incumbents have 6 choice alternatives (5 weekends within a season and an “exit” option) whereas entrants one more alternative of “no-entry”. The same argument applies to the other equations in the later text.

In this equation, D_w contains three sets of dummy variables that capture the anticipated payoff for the “no entry” option and the anticipated underlying demand for the “holiday” and “non-holiday” weekends. The anticipated payoff for the “exit” option or any other weekends outside of the targeted season is benchmarked as 0 for identification purposes.

For each alternative weekend within a targeted season (w = 1 ~ 5), n_{iw_sg} and n_{iw_dg} are numbers of competitor movies of the same and different genres in comparison with movie i, all targeting weekend w; for no entry or exit options, they are simply zeros. We separate out competitor movies of the same genres vs. different genres since these two groups of competitors may well have different effects on the studio managers' release date decisions.

γ represents the effects of switching on studio managers' decisions. As we mentioned in the earlier sections, switching the targeted release dates would incur various costs. I_{switch} is an indicator variable taking the value of 1 if play i selects weekend w, which is different from her most choice of the release date[19].

[18] This anticipated payoff can also be considered as the utility for a studio manager to maximize the possible success of her movie, by analogy of the discrete choice modeling framework in which a consumer maximizes her utilities in selecting a product or brand among several alternatives.

[19] We do not explicitly model the switching costs in our current model due to the lack of data or reasonable measures of the magnitude of these switching costs. We therefore simply use a dummy variable to indicate

The competitive state s contains all the common knowledge state variables observable to all players, or in other words, the competitor movies targeting each alternative weekend. That is, $s = \{n_{iw\_sg}, n_{iw\_dg}, \forall i, w\}$.

Now we can write down player i's value function for alternative weekend w as

(2)

$$V_i(a_i = w, s, \varepsilon_{iw}; P_{-i}) = E\pi_i(a_i = w, s) + \varepsilon_i(a_i = \mathrm{w}) + \delta \sum_{s'} [\int V_i(s', \varepsilon_i^{'}; P_{-i}) g(\varepsilon_i^{'}) d\varepsilon_i^{'}] f_i(s' | s, a_i = w; P_{-i})$$

OR simply $V_{iw}(s, \varepsilon_{iw}; P_{-i}) = \mathrm{E}\pi_{\mathrm{iw}}(s) + \varepsilon_{iw} + \delta \sum_{s'} V_i^{'}(s'; P_{-i}) f_i(s' | s, w; P_{-i})$

In the above equations, we use "prime" to indicate all the values for the future or next decision period. This action-specific or alternative weekend-specific value function consists of both the expected payoff for the current period $\mathrm{E}\pi_{\mathrm{iw}}(s)$, as we have introduced earlier, and the discounted expected future value $\delta \sum_{s'} V_i^{'}(s'; P_{-i}) f_i(s' | s, w; P_{-i})$.

This expected future value is computed as a weighted sum of the possible future values given the possible future states, weighted by the probabilities of reaching these future states. $f_i(s' | s, w; P_{-i})$ is player i's perceived transition probability from the current state s to the future state s' given her own choice of alternative weekend w and her conjectures of other competitors' choices probabilities P_{-i} .

The discount factor δ is typically fixed as .99. When we constrain the discount factor to be zero, we obtain an alternative model called "myopic" since it represents a situation where the studio managers do not account for the effects of their current actions on the future competition.

ε_{iw} is conceptually interpreted as player i's private information only known to herself and observed by her competitors only in distribution. It might include private preferences for player i to select an alternative weekend w to release the movie (Seim

whether the current choice represents a switch from the most recent choice of the release date and use γ to capture the effects of switching on release date decisions.

2001 and 2002 working paper; Einav 2002 working paper). In our context, it can represent a variety of player i's private information of or preference for weekend w due to, say her preference to release a movie (such as a sequel or a movie of a certain theme) in a specific weekend[20]. ε_{iw} is assumed to follow Type I Extreme Value distribution that leads to the close-form choice probabilities for each alternative weekend in the conditional logit framework (McFadden 1984).

Given a specific competitive state, player i's value is defined the highest among all the alternative weekend-specific values:

(3)
$$V_i(s,\varepsilon_i;P_{-i}) = \max_{a_i}\{E\pi_i(a_i = w,s) + \varepsilon_i(a_i = \mathrm{w}) + \delta\sum_{s'}[\int V_i(s',\varepsilon_i^{'};P_{-i})g(\varepsilon_i^{'})d\varepsilon_i^{'}]f_i(s'|s,a_i = w;P_{-i})\}$$

We integrate the above equation over the private information to obtain the value function as a function of only the common-knowledge state variables.

(4)
$$V_i(s;P_{-i}) = \int \max_{a_i}\{E\pi_i(a_i = w,s) + \varepsilon_i(a_i = w) + \delta\sum_{s'}V_i(s';P_{-i})f_i(s'|s,a_i = w;P_{-i})\}g_i(d\varepsilon_i)$$

Given the Type I Extreme Value distribution of ε_i,

(5)
$$V_i(s;P_{-i}) = \ln[\sum_{a_i}\exp\{(\bar{z}_i(a_i = w,s)\theta_i + \delta\sum_{s'}V_i(s';P_{-i})f_i(s'|s,a_i = w;P_{-i})\}]$$

where $\bar{z}_i(a_i = w,s) = [D_w, \mathrm{n_{w\_sg}}, \mathrm{n_{w\_dg}}, I_{switch}]$ and $\theta = [\alpha\ \beta_{sg}\ \beta_{dg}\ \gamma\ ]'$.

This is a contraction mapping in the space of value functions in the sense that the value function appears on both sides of the equation. The contraction mapping provides a convenient method to numerically solve the value function. That is, we can input an initial value on the right hand side (RHS thereafter) and solve the value function on the left hand side (LHS thereafter) and further input this solved value into the RHS. Such iterations will continue until the convergence between the RHS value function and the

[20] Each studio also has a reasonable estimate of the rivals' production costs after the production is over, and studios have common estimates of how well the movies might do. As we will explain shortly, our current model formulates the expected payoff or success of a movie as being a function of the number of rivals and does not control for their possible qualities or production costs. In future research, we plan to expand our model to account for these quality and cost differences.

solved value function on the LHS. By Blackwell Theorem (Blackwell 1965), for each player i, there is a unique function $V_i(s;P_{-i})$ that solves the above equation (5) for a given set of strategy functions or decision rules by each of the players. Please see Appendix A2 for an alternative way to compute this value function proposed by Aguirregabiria and Mira (2002 and 2003 working paper). We use this alternative method to compute the value functions and we will further elaborate on why we use this method in section 5.4.

5.3 The choice probabilities and the Markov Perfect Equilibrium (MPNE):

Given that all other players follow their strategies, the best response of player i is:

(5) $$\phi_i(s;P_{-i}) = \arg\max_{a_i}\{V_i(a_i = w, s; P_{-i})\}$$

A Markov Perfect Nash Equilibrium is defined as a set of strategies a* such that for any player i and for any state s, $a_i^*(s) = \phi_i(s;P_{-i}^*)$.

The MPNE can be also represented in the probability space (Milgrom and Weber 1985). In our context of multinomial logit model, the probability for player i to take action a_i is:

(7) $$\Phi_i(a_i = w \mid s;P_{-i}) = \frac{\exp\{E\pi_i(a_i = w,s) + \delta\sum_{s'}V_i(s';P_{-i})\,f_i(s' \mid s,a_i = w;P_{-i})\}}{\sum_{a_j}\exp\{E\pi_i(a_j,s) + \delta\sum_{s'}V_i(s';P_{-i})\,f_i(s' \mid s,a_j;P_{-i})\}}$$

Recall that the equilibrium is characterized by the value function and the transition probabilities computed from the estimated choice probabilities for all players. Therefore, given their inter-dependence, we need to solve for both of them simultaneously to fully characterize the equilibrium. This involves simultaneously solving equations (5) and (7). This is a "coupled fixed point problem". That is, given a set of choice probabilities we compute the transition probabilities and then obtain from equation (5) the value functions as solutions to the fixed point problem; and then given these value functions we obtain the best response choice probabilities defined in equation (7) that are further used to compute the transition probabilities to be input back into equation (5). This process will continue until we obtained converged value functions and choice probabilities. Instead of solving the above "coupled fixed point problem", we apply the method proposed by Aguirregabiria and Mira (2002 and 2003 working paper) in our analysis (again, please refer to the Appendix A2 for more details). We will explain the rationale behind it next.

5.4 Computational costs and estimation methods

There has been considerable progress in the computational techniques of the discrete choice dynamic programming models. Rust (1987) introduced the conditional independence assumption and the nested fixed point algorithm (NFXP) that greatly reduce the dimension of the dynamic programming problem and obtain maximum likelihood estimates. Hotz and Miller (1993) introduced an even simpler estimator than NFXP, the conditional choice probabilities estimator (CCP) which does not require solving the fixed point problem yet still obtain consistent and asymptotically normally distributed estimators. KPIE (k-stage policy iteration estimator) introduced by Aguirregabiria and Mira (2002) bridged the gap between NFXP (when $k = \infty$) and CCP (when k = 1) and nested both as extreme cases. KPIE avoids repeated solution of the fixed point problem at the expense of a larger number of likelihood maximization iterations. Therefore, KPIE would be computationally faster than NFXP if the fixed point iterations are more costly than the likelihood iterations. Aguirregabiria and Mira (2002) demonstrated in Monte Carlo experiments that KPIE produced maximum likelihood estimator (MLE) 5 to 15 times faster than NFXP. In addition, compared to CCP which is equivalent to KPIE with k = 1, KPIE can improve the finite sample properties of the estimator significantly even by extending k = 1 to k = 2.

A serious issue in applying dynamic programming tools is that the computational cost increases with the number of players in the game. This is because the dynamic programming technique (such as NFXP) used to compute the value functions and therefore the choice probabilities for the computation of MLE has to be repeated applied to each player and each state in the state space whose dimension exponentially increases in the number of players. This is commonly known as the “curse of dimensionality”. In our application, since the number of players and the number of choice alternatives are relatively small, KPIE is sufficient to compute the parameter estimates. However, if the number of players or the number of choice alternatives increases, we can apply the simulated version of KPIE introduced by Aguirregabiria and Mira (2003 working paper) to address the problem of the curse of dimensionality.

Therefore, we develop a set of MATLAB codes and apply KPIE to estimate the set of parameters capturing the effects of anticipated demand, competition, and switching in the proposed dynamic model. The log likelihood function in our context is:

$$(8) \qquad LL(P^*;\ \theta) = \sum_{g=1}^{G}\sum_{i=1}^{N}\sum_{t=1}^{T_g}\sum_{w=1}^{W} y_{gitw} * \ln \Psi_{gitw}(\ P^*;\ \theta) \text{ and } \hat{\theta}_{MLE} = \arg\max_{\theta} LL(P^*;\ \theta)$$

where y_{gitw} is an indicator which takes the value of 1 is player i chose choice alternative w in decision period t of game g.

Please refer to Figure 8 for the detailed KPIE procedure we have used.

------------- Figure 8 -----------------

5.5 Ensuring uniqueness of the equilibrium

Multiple equilibria pose a common problem in most empirical games where best response functions are non-linear in other players' actions. There are two main approaches that address this problem in discrete choice dynamic games. The first approach is to impose restrictions in order to guarantee the uniqueness of the equilibrium. For instance, equilibrium is unique if the strategic iteration has a recursive structure (Heckman 1978). However, such assumptions impose strong restrictions on the possible strategic interactions in many empirical applications. A second approach is to exploit only those predictions of the game that are invariant across multiple equilibria, for instance, the number of entrants in static models of firm entry (Bresnahan and Reiss 1990; Berry 1992). However, outcomes of the games that are invariant across multiple equilibria do not always exist.

Aguirregabiria and Mira (2003 working paper) have set forth three assumptions for the identification of the equilibrium actually played from the data and therefore guarantee the consistency of the estimators. First, players are assumed to have incomplete information and private information that is independent across all players. Under this assumption, MPNE can be represented in the space of players' choice probabilities conditional on common knowledge state variables. Second, common knowledge state variables are assumed to have a discrete and finite support. Finally, all observations in the data are assumed to be generated from the same dynamic equilibrium (or, if they are from different equilibria, it is known that which observations belong to which equilibrium). In other words, the choice probabilities are equilibrium probabilities and not a mixture of equilibrium probabilities. Aguirregabiria and Mira (2003 working paper) have demonstrated that under these assumptions, it is possible to identify the equilibrium actually played in the data.

5.6 Model comparison

We further compare the proposed dynamic model under the MPNE framework with two other alternative models.

One is the "myopic" model obtained by constraining the discount factor δ in the value function to be zero; therefore the myopic model is nested within the dynamic models. In this model, studio managers do not account for the effects of current actions on the future competition therefore ignore the effects of future values on the current decisions. Or in other words, they only maximize the expected payoff for the current period instead of the discounted sum of the expected payoffs for the entire decision horizon.

The second model is called a "static" model. It is a one-shot game for each decision period, in which studio managers only maximize the expected payoff for the current period. They further ignore the history of the pre-announced release date decisions and do not account for the effects of current actions on the future competition.

Equation (7) below is player i's expected payoff for alternative weekend w, given the current competitive state s:

$$\text{(7)} \qquad \forall i, \quad E\pi_{iw}(s) \ = \alpha_w D_w + \beta \ En_{iw} = \alpha_w D_w + \beta \ [(N-1) * P_w^* + 1]$$

That is, the competitive effects are captured by the expected number of competitors player i faces, which is computed as the total number of player i's competitors (N – 1) multiplied by conjectured probability of choosing alternative by each symmetric competitive player. This conjectured probability, or in equilibrium, the equilibrium choice probability has the logit format, that is,

$$\text{(8)} \ P_w^* = \frac{\exp[\mathrm{E}\pi_w]}{\sum_{w'} \exp[\mathrm{E}\pi_{w'}]} = \frac{\exp\{\alpha_w D_w + \beta \ [(N-1) * P_w^* + 1]\}}{\sum_{w'} \exp\{\alpha_{w'} D_{w'} + \beta \ [(N-1) * P_{w'}^* + 1]\}} .$$

When we substitute $\mathrm{E}\pi_w$ in the above equation (8) with that in equation (7), we obtain a "fixed point" in the sense that the equilibrium choice probability P_w^* appears on both the RHS and LHS of the equation; this again facilitates the computation of the equilibrium choice probability P_w^*. We apply the Fixed Point Algorithm (similar to that used in Seim 2001 and 2002 working papers) to estimate the parameters. Please see Figure 9 for further details of this algorithm.

------------- Figure 9 ------------------

We randomly selected a set of 40 games for model calibration and 6 games for the prediction exercise. We further use three alternative specifications of the current-period expected payoff functions (see the equation 9 below) when comparing the three alternative models, the dynamic model, myopic model, and static model, in both model calibration (the in-sample fit) and the prediction exercise (the out-of-sample fit).

$$\begin{aligned} &E\pi_{iw}(s) = \alpha_w D_w + \beta n_{iw} \quad \text{OR} \\ (9)\quad &E\pi_{iw}(s) = \alpha_w D_w + \beta n_{iw} + \gamma I_{switch} \quad \text{OR} \\ &E\pi_{iw}(s) = \alpha_w D_w + \beta_{sg} n_{iw\_sg} + \beta_{dg} n_{iw\_dg} + \gamma I_{switch} \end{aligned}$$

That is, we sequentially account for various factors that affect the expected payoffs of each alternative weekend. In the first specification, only the anticipated demand and the competitive effects measured by the number of competitor movies targeting the same weekend w are included. In the second specification, the switching effects are added. The third specification is the full specification with the genre effects further incorporated. When we compare the dynamic model, myopic model, and static model in both in-sample fit and out-of-sample prediction, we compare them across each of the above three specifications of the value functions.

Finally, to address the second research question we raised in section 2 (that is, whether our inference about the strategic interactions among studio managers would differ if we use a static model to analyze only the final release date decisions and ignore the history or the entire sequence of release date decisions that endogenously determine the final release dates), we further estimate the static model using only the final release dates, as if studio managers simultaneously make one-shot decisions of the release dates. We then compare the parameter estimates from this static model and our proposed dynamic model to see if our inferences might differ.

6. EMPIRICAL RESULTS

Corresponding to our research objectives, our estimation results help address the following research questions:

Research question 1: Do studio managers account for the dynamics in the competitive set composition while selecting the release dates?

As we mentioned in section 5.6, we compare the dynamic model with both the static model and the myopic model across three sets of different specifications of the payoff or value functions. We use the Bayesian Information Criterion (BIC) to measure the in-sample fit of the three models; a less negative or closer-to-zero BIC indicates a better fit of the model.

Table 4 illustrates that when we sequentially incorporate more factors into the payoff or value function, all three models - the dynamic model, myopic model, and static model, have shown an improved in-sample fit. More importantly, across all three specifications of the payoff or value functions, the dynamic model outperforms the myopic model that maximizes only the current-period expected payoff and therefore does not account for the effects of the contemporaneous actions on future competitive set composition. The dynamic model further outperforms the static model that accounts for neither the game history nor the inter-temporal linkage between the current actions and future competition.

------------- Table 4 ------------------

These comparisons illustrate the superiority of the dynamic model in capturing the key features of the pre-announcement game among studios. That is, studio managers are forward-looking and maximize the inter-temporal expected payoffs when selecting the release dates for their movies by accounting for the dynamic changes of the competitive sets in the presence of competitive entry and exit over multiple periods.

Using an appropriate model, that is, the dynamic model in our context, to capture the complicated release date pre-announcement game is critical in the sense that it can lead to a more accurate inference of the studios' decision processes and strategic interactions, and can further increase a manager's capability to more accurately forecast the competitors' release date decisions and responses to pre-announced release dates.

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------------- Table 5 -----------------

The effects we have identified that might contribute to the studios' release date decisions and therefore strategic interactions, that is, the effects of the anticipated underlying consumer demand for movies, competition, switching, and genres, all turn out to be significant. Table 5 lays out the estimated directions and magnitudes of these key factors across the aforementioned three alternative specifications of the payoff or value functions in the proposed dynamic model.

These results show that: (i) studios anticipate that the underlying consumer demand for movies over the holiday weekends is always much higher than that over the non-holiday weekends; that is, $\alpha_{holiday}$ typically doubles $\alpha_{non\_holiday}$ in magnitude; this illustrates why managers are on average more willing to select a holiday weekend to release their new movies; (ii) the anticipated or perceived underlying demand over both holiday and non-holiday weekends contributes positively to the expected payoff or value of any specific weekend; that is, the signs of $\alpha_{holiday}$ and $\alpha_{non\_holiday}$ are both positive; (iii) competition always reduces the expected payoff or value of an alternative weekend; that is, the competitive effect β is always negative, which further illustrates a significant tradeoff between inherent attractiveness or the anticipated underlying demand over the holiday weekends and the negative competitive effects induced by more rivals competing for these attractive holiday weekends; (iv) switching the targeted release dates reduces the expected payoff; that is, the switching effect γ is always negative, though its magnitude is not as large as that of the competitive effects; this indicates that studio managers are indeed concerned about the switching costs and further illustrates that the game play is serious instead of cheap talk; (v) the competition from the same-genre competitors reduces the expected payoff almost twice as much as that from the competitors of different genres (β_{sg} is almost twice as large as β_{dg} in the absolute magnitude when we separated out the competitive effects from movies of the same vs.

different genres); in other words, having one same-genre competitor that targets the same weekend is almost as damaging as having two competitor movies of different genres targeting that weekend; therefore studio managers try to avoid head-to-head competition, particularly with movies of the same genre.

Research question 2: Will our inference about the release date decisions and strategic interactions among studios differ if we ignore the competitive dynamics?

We compare the estimation results between the static model that analyzes only the actual release dates and the dynamic model that analyzes the entire history of the pre-announced release dates; both have incorporated the effects of the anticipated demand and the competition.

We compare the two models since (i) the vast majority of the competitive models used to draw inference of and forecast the strategic interactions in the current marketing and economics literature are static; (ii) almost all existent studies of the motion picture industry focus entirely on the final release dates even though they are endogenously determined by a long history of a pre-announcement game. Therefore, we compare the magnitude of the estimated effects of underlying demand and competition between the static model and the dynamic model. We hope to gain some insights into whether accounting for the history or entire sequence of the release date decisions, hence the competitive dynamics, would lead to more accurate inferences of the studios' decision processes and strategic interactions.

The static model produces statistically significant and intuitive parameter estimates. Again, we can see the tradeoff between the positive effects of the anticipated underlying demand (1.01 for non-holiday weekends and 1.22 for holiday weekends) and the negative effects of competition (-.21) on the expected payoffs. Again, studio managers perceive higher underlying demand over the holiday weekends (1.22) than over the non-holiday weekends (1.01). Finally, the dynamic model fits the data better than the static model in terms of the per-observation BIC.

The interesting finding here is that, compared to the dynamic model, the static model (i) overstates the anticipated underlying demand for both holiday and non-holiday weekends; (ii) understates the competitive effects; and (iii) understates the perceived gap in the underlying demand between the holiday and non-holiday weekends. Such findings are likely due to the fact that studios make strong efforts to avoid head-to-head competition in the early stage of the pre-announcement game but towards the end crowd into the non-holiday weekends within the holiday season. This is consistent with our observation that the numbers of movies actually released over holiday vs. non-holiday weekends do not differ much.

This comparison illustrates that ignoring the competitive dynamics and not accounting for the entire history of release date decisions that ultimately lead to the final release dates may provide biased parameter estimates and therefore lead to inaccurate inferences of studio managers' decision processes and strategic interactions, particularly in an environment where competitive states or competitive sets dynamically change from one period to another as competitors enter, exit, or change their strategic actions.

-------------- Table 6 ------------------

Research question 3. Can accounting for the competitive dynamics improve a studio manager's prediction of competitors' decisions or responses to the pre-announced release dates?

We use both the Mean Absolute Deviation (MAD) and the Hit Ratio to measure the performance of the out-of-sample prediction of various models. A perfect prediction is achieved when the MAD equals zero or the hit ratio equals 1. An MAD close to .5 or a hit ratio close to 0 indicates a poor prediction.

-------------- Table 7 ------------------

Table 7 illustrates that across all three alternative specifications of the payoff or value functions, the out-of-sample prediction measured by both the MAD and the Hit Ratio is improved across all three models, the static model, the myopic model, and the dynamic model. These results illustrate that these key factors that we have identified, the anticipated underlying demand, competition, genres, and switching costs, all contribute to the improvement of the predictive power of these models.

More importantly, for each of the alternative specifications of the payoff functions, the dynamic model always best predicts the competitor responses to pre-announced release date decisions. When we use the full specification of the payoff or value function, we can accurately forecast as high as 64.4% of the competitive release date decisions. This is consistent with our earlier result that the dynamic model best captures the key features of the dynamic pre-announcement game. The increased predictive power improves a studio's release timing decisions and ultimately the revenues.

7. CONCLUSION

In this research, we study how studios strategically select the targeted release dates, or the competitive sets, of their movies, in the presence of frequent competitive entry and exit prior to the actual release of these movies. The insights we develop from analyzing these strategic interactions can further help a studio manager select the optimal release timing under various competitive states by more accurately forecasting rival studios' strategic actions.

We construct a model under the general framework of Markov Perfect Nash Equilibrium (MPNE) to capture the release date pre-announcement game with *forward-looking* studios *simultaneously* making and pre-announcing the *discrete* entry, exit, and release date decisions over *multiple* periods. We apply a newly developed methodology (Aguirregabiria and Mira 2002) to empirically estimate the proposed dynamic model using a data set of pre-announced release dates from the U. S. motion picture industry. We further compare the dynamic model with two other conventionally used models, the static and the myopic model, in both the in-sample fit and out-of-sample prediction.

Our results demonstrate that studios are forward-looking and maximize the inter-temporal expected payoffs during decision making; ignoring such critical competitive dynamics produces inaccurate inferences on studios' decision processes and strategic interactions; and accounting for such competitive dynamics increases a studio's predictive power of competitor decisions and responses to pre-announced release date decisions. Therefore, our study can help improve the studio's managerial decision making of the release timing and hence the potential revenues.

Substantively, we contribute to the marketing literature, particularly the literature of motion picture research and the new product pre-announcement research by analyzing a very critical competitive process among various studios in the U.S. motion picture industry – the selection and pre-announcement of release dates for their new movies prior to the actual releases, particularly in the presence of frequent competitive entry and exit. Our research further enriches the empirical industrial organization literature dominated by the static competitive models by establishing a dynamic model that captures the competitive dynamics induced mainly by supply-side selections of competitive sets and by further illustrating the critical role of such competitive dynamics in improving the accuracy of inferences of competitive behavior and the predictive power of competitor moves.

Methodologically, our research contributes to the marketing literature by illustrating an empirical application of the MPNE framework to a discrete choice dynamic game; this research also represents the first empirical application of a newly developed estimation procedure proposed by Aguirregabiria and Mira (2002) to the estimation of such a discrete choice dynamic game within a marketing context.

Managerially, our research contributes to the industrial practice by (i) identifying a set of key factors such as genres and switching costs that influence the studios' release date decisions and strategic interactions, (ii) measuring the directions and relative magnitudes of these factors that can be further used to conduct counter-factual experiments regarding the effects of the changes of these factors on rival studios' release date decisions and switching patterns useful for the manager's decision making; (iii) improving a manager's predictive power of competitor movies by accounting for the competitive dynamics. The proposed dynamic model can be further incorporated into a decision support system to either automate a studio manager's release date decisions or to serve as a reference guide to help the manager avoid over-reaction to competitive entry/exit and therefore avoid unnecessary switching costs. These improved release timing decisions should translate to improved box office revenues critical for the studios in this industry.

There are several possible extensions to our models. First, we can incorporate other factors that may affect the release date decisions and the competition among studios, such as the production costs and the estimated quality differences among competitor movies. Second, we can incorporate the competitive effects from movies targeting the neighboring, not just the same opening, weekend. Third, we can further incorporate the analysis of historical box office data and help managers more accurately forecast not only the competitors' release date decisions but also the "true" underlying consumer demand for movies across various weekends. We hope to be able to provide managers with useful rules of thumb on how to reduce the gap between their perceived demand and the true underlying demand and hence improve their release date decisions and revenues. Finally, our analytical framework and empirical estimation methods can be generalized to studying other research problems in a variety of industries with minor modifications appropriate for different industrial contexts, such as music CD and new book releases, TV programming, firm location choices, domestic and international diffusion strategies, merger & acquisition, and so on.

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Appendix:

A1. Derivation of the Bellman Equation

During the release date pre-announcement game, each studio manager computes the value for each alternative weekend and selects the one with the highest value to release her movie.

In this appendix, we will illustrate how to compute this value as a discounted sum of the expected payoffs for the movie over the entire decision horizon. They are "expected" payoffs since the final "actual" payoff is realized only when the movie is actually released.

In each decision period, studio manager i's action or selection of an alternative weekend w adjusts the expected payoffs for the movie i since weekend w may represent a different anticipated underlying demand, have a different competitive set, and incur some switching costs. To simplify the notation, we drop the player subscript and the alternative weekend subscript.

For each decision period, say period 1, we use the Bellman equation below to compute the value function for this period: $V_1 = E\pi_1 - E\pi_0 + \delta V_2$ where $E\pi_1 - E\pi_0$ is the current-period adjustment of the expected payoff compared to the last period; δV_2 is the discounted expected future value for the next period.

When we recursively substitute the value functions for the future periods, we obtain a discounted sum of all values across the entire decision horizon. This is why the Bellman Equation is equivalent to or concisely captures the discounted sum of values in all decision periods.

$$
\begin{aligned}
V_1 &= E\pi_1 - E\pi_0 + \delta V_2 \\
&= E\pi_1 - E\pi_0 + \delta(E\pi_2 - E\pi_1 + \delta V_3) = E\pi_1 - E\pi_0 + \delta(E\pi_2 - E\pi_1) + \delta^2 V_3 \\
&= \ldots \quad = \sum_{t=1}^{T} \delta^{t-1}(E\pi_t - E\pi_{t-1})
\end{aligned}
$$

In addition, maximizing the value function in the above specification $V_1 = E\pi_1 - E\pi_0 + \delta V_2$ is equivalent to maximizing the value function $V_1 = E\pi_1 + \delta V_2 = \sum_{t=1}^{T} \delta^{t-1} E\pi_t$ or $V = E\pi + \delta V^{'}$ used in our paper since:

$$
\begin{aligned}
V_1 &= E\pi_1 - E\pi_0 + \delta V_2 \\
&= E\pi_1 - E\pi_0 + \delta(E\pi_2 - E\pi_1 + \delta V_3) = E\pi_1 - E\pi_0 + \delta(E\pi_2 - E\pi_1) + \delta^2 V_3 \\
&= -E\pi_0 + (1-\delta)[E\pi_1 + \delta E\pi_2 + \delta^2 E\pi_3 + ... + \delta^{T-2} E\pi_{T-1}] + \delta^{T-1} E\pi_T \\
&= -E\pi_0 + (1-\delta)\sum_{t=1}^{T-1} \delta^{t-1} E\pi_t \ + \delta^{T-1} E\pi_T
\end{aligned}
$$

A2. An alternative method to compute the value function and represent the equilibrium choice probabilities

In order to avoid solving the fixed point problem to obtain the value functions, we choose to use an alternative best response mapping as in Aguirregabiria and Mira (2003), who demonstrated that this alternative can provide significant computational gains.

Let $P^* \equiv \{P^*(a,s)\}$ be equilibrium choice probabilities which include both P_i^* (the equilibrium choice probabilities for player I) and P_{-i}^* (the equilibrium choice probabilities for all the other competitors). Let $V_1^*, V_2^*, ..., V_N^*$ be the N players' equilibrium value functions. We can re-write the equation (4) as:

(a2-1) $$V_i^*(s) = \sum_{a_i \in A} P_i^*(a_i,s)[E\pi_i(a_i,s) + e_i(a_i,s;P_i^*) + \delta \sum_{s' \in S} V_i^*(s') \bar{f}(s' \mid s; a_i, P_{-i}^*)]$$

where $e_i(a_i,s;P_i^*) = E[\varepsilon_i(a_i,s)] =$ Euler Constant $- \ln(P_i^*(a_i,s))$, given the Type I Extreme Value distribution of $\varepsilon_i(a_i,s)$.

Given a set of equilibrium probabilities P*, equation (a2-1) describes a vector of values V_i^* as the solution to a system of linear equations, which in vector form is:

(a2-2) $$[I - \delta \sum_{a_i \in A} P_i^*(a_i) * F(a_i, P_{-i}^*)] V_i^* = \sum_{a_i \in A} P_i^*(a_i) * [E\pi_i(a_i) + e_i(a_i; P_i^*)]$$

where * in equation (a2-2) is the element-by-element or Hadamard product. If we use M to denote the dimension of the state space and use K to denote the number of parameters to be estimated in the model, $F(a_i, P_{-i}^*)$ is the M x M matrix of transition probabilities from player i's perspective, given player i's action and other players' choice probabilities conjectured by player i. $E\pi_i(a_i) = \bar{z}(a_i)\theta$ is an M x 1 vector of expected payoffs; where $\bar{z}(a_i)$ is the M x K matrix of regressors with $\bar{z}_i(a_i,s) = [D_w \ \mathrm{n}_{\mathrm{w\_sg}}, \mathrm{n}_{\mathrm{w\_dg}}, I_{switch}]$ in each row; and $\theta = [\alpha \ \beta_{sg} \ \beta_{dg} \ \gamma \ ]'$ is a K x 1 vector of all parameters to be estimated in the model.

The solution to the above equation (a2) is:

(a2-3) $$V_i^*(P^*) = [I - \delta \sum_{a_i \in A} P_i^*(a_i) * F(a_i, P_{-i}^*)]^{-1} \{ \sum_{a_i \in A} P_i^*(a_i) * [E\pi_i(a_i) + e_i(a_i; P_i^*)] \}$$
$$= W_i^y(P^*)\theta + W_i^e(P^*)$$

where $W_i^y(P^*) = [I - \delta \sum_{a_i \in A} P_i^*(a_i) * F(a_i, P_{-i}^*)]^{-1} \sum_{a_i \in A} P_i^*(a_i) * \bar{z}_i(a_i)$ and

$$W_i^e(P^*) = [I - \delta \sum_{a_i \in A} P_i^*(a_i) * F(a_i, P_{-i}^*)]^{-1} \sum_{a_i \in A} P_i^*(a_i) * (\text{Euler Constant - ln}(P_i^*(a_i)).$$

We can now characterize the MPNE as a set of equilibrium strategies or choice probabilities $P_i^*(a_i) = \Psi(P_i^*(a_i))$, which, given the Type I Extreme Value distribution of ε_i, in the compact matrix format is:

(a2-4)

$$\Psi_i(a_i; P^*) = \frac{\exp\{\bar{z}(a_i)\theta + \delta F(a_i; P_{-i}^*) V_i^*(P^*)\}}{\sum_{a_j \in A} \exp\{\bar{z}(a_j)\theta + \delta F(a_j; P_{-i}^*) V_i^*(P^*)\}} = \frac{\exp\{\tilde{z}(a_i; P^*)\theta + \tilde{e}(a_i; P^*)\}}{\sum_{a_j \in A} \exp\{\tilde{z}(a_j; P^*)\theta + \tilde{e}(a_j; P^*)\}}$$

where $\tilde{z}(a_i; P^*) = \bar{z}_i(a_i) + \delta F(a_i; P_{-i}^*) W_i^y(P^*)$ and $\tilde{e}(a_i; P^*) = \delta F(a_i; P_{-i}^*) W_i^e(P^*)$.

Table 1. Historical statistics in the motion picture industry

Year	U.S. Population (by July 1 of each year; in millions) *	Number of Movies Released **	Average Ticket Price (in $) **	Box Office Grosses in Our EDI Data (in billions $)	Total U.S. Box Office Grosses (in billions $) **	Total U. S. Admissions (in billions) **
1990	249.44	222	4.22	4.53	5.02	1.19
1991	252.13	224	4.21	4.32	4.8	1.14
1992	254.99	214	4.15	4.61	4.87	1.17
1993	257.75	227	4.14	4.97	5.15	1.24
1994	260.29	233	4.08	5.09	5.4	1.29
1995	262.76	246	4.35	5.38	5.49	1.26
1996	265.19	262	4.42	5.70	5.91	1.34
1997	267.74	250	4.59	6.07	6.37	1.39
1998	270.30	264	4.69	6.54	6.95	1.48
1999	272.88	254	5.06	7.27	7.45	1.47
2000	281.32	266	5.39	7.58	7.67	1.42
2001	285.32	255	5.65	8.03	8.41	1.49

* Source: the U.S. Census Bureau
** Source: NATO (National Association of Theater Owners) and MPAA (Motion Picture Association of America)

Table 2. An example of the release date pre-announcement game

Title	***LEGALLY BLONDE***	***AMERICA'S SWEETHEARTS***	***CATS & DOGS***
Studio (product costs)	MGM/UA ($ 18M)	Sony ($ 48M)	WB ($ 60M)
Pre-announcement Date	Announced Release Date		
10/1/00	Year 01	7/20/01	-
1/1/01	Summer 01	7/4	5/25/01
3/15/01	Summer 01	7/4	**7/4**
4/1/01	July 01	7/4	7/4
4/15/01	7/13	**7/13**	7/4
5/1/01	7/13	**7/20**	7/4
Actual Release Date	7/13	7/20	7/4

Table 3. Distribution of the selected movies across studios

Studio	Number of Titles
BUENA VISTA (Disney)	116
DREAMWORKS	14
MGM/UA	53
MIRAMAX	63
NEW LINE	63
ORION	15
PARAMOUNT	85
SONY	136
TWENTIETH CENTURY FOX	72
UNIVERSAL	82
WARNER BROTHERS	105
Subtotal	804 (87.4 %)
Other Studios	116 (12.6 %)
Total	920 (100 %)

Table 4. Model comparison: in-sample fit (BIC)

Bayesian Information Criterion (BIC) = log likelihood – log (# obs.) * (# parameters) / 2

Model	**(1) anticipated demand and competitive effects** (# competitors) $\alpha D + \beta n$	**(2) = (1) + switching effects** $\alpha D + \beta n + \gamma I_{switch}$	**(3) = (2) + competitive effects (# competitors by genres)** $\alpha D + \beta_{sg} n_{sg} + \beta_{dg} n_{dg} + \gamma I_{switch}$
Static	-18,738	-18,170	-17,156
Myopic	-18,222	-17,093	-16,542
Dynamic	-15,331	-14,025	-13,438

Table 5. Parameter estimates for the dynamic models

Parameter ⬇	**Model** ➡	**(1) = anticipated demand + competitive effects** (# competitors) $\alpha D + \beta n$	**(2) = (1) + switching effects** $\alpha D + \beta n + \gamma I_{switch}$	**(3) = (1) + competitive effects (# competitors by genres)** $\alpha D + \beta_{sg} n_{sg} + \beta_{dg} n_{dg} + \gamma I_{switch}$
Anticipated demand	$\alpha_{non\_holiday}$	0.46 *	0.42 *	0.51 *
	$\alpha_{holiday}$	1.07 *	1.13 *	1.19 *
Competitive effects (# competitors)	β	-0.30 *	-0.24 *	-
Switching effects	γ	-	-0.17 *	-0.13 *
Competitive effects (# competitors by genres)	β_{sg}	-	-	-0.34 *
	β_{dg}	-	-	-0.19 *

* significant at .01 level.

Table 6. Comparison of parameter estimates for the dynamic vs. static model that analyzes only the actual release dates

Parameter ⬇	Model ➡	Static (analyzing only actual release dates)	Dynamic (analyzing the entire history of pre-announced release dates)
Anticipated demand	$\alpha_{non\_holiday}$	1.01 *	0.46 *
	$\alpha_{holiday}$	1.22 *	1.07 *
Competitive effects (# competitors)	β	-0.21 *	-0.30 *

* significant at .01 level.

Table 7. Model comparison: out-of-sample prediction (MAD and Hit Ratio)

Mean Absolute Deviation (MAD)
= sum [abs (predicted probability - observed choice)] / #obs.

Hit Ratio = proportion of correct predictions

Model	**(1) anticipated demand and competitive effects** (# competitors) $\alpha D + \beta n$	**(2) = (1) + switching effects** $\alpha D + \beta n + \gamma I_{switch}$	**(3) = (2) + competitive effects (# competitors by genres)** $\alpha D + \beta_{sg} n_{sg} + \beta_{dg} n_{dg} + \gamma I_{switch}$
		MAD	
Static	.191	.182	.163
Myopic	.174	.151	.132
Dynamic	.150	.122	.101
		Hit Ratio	
Static	.291	.352	.414
Myopic	.332	.411	.483
Dynamic	.433	.522	.644

Figure 1. Major players in the motion picture industry

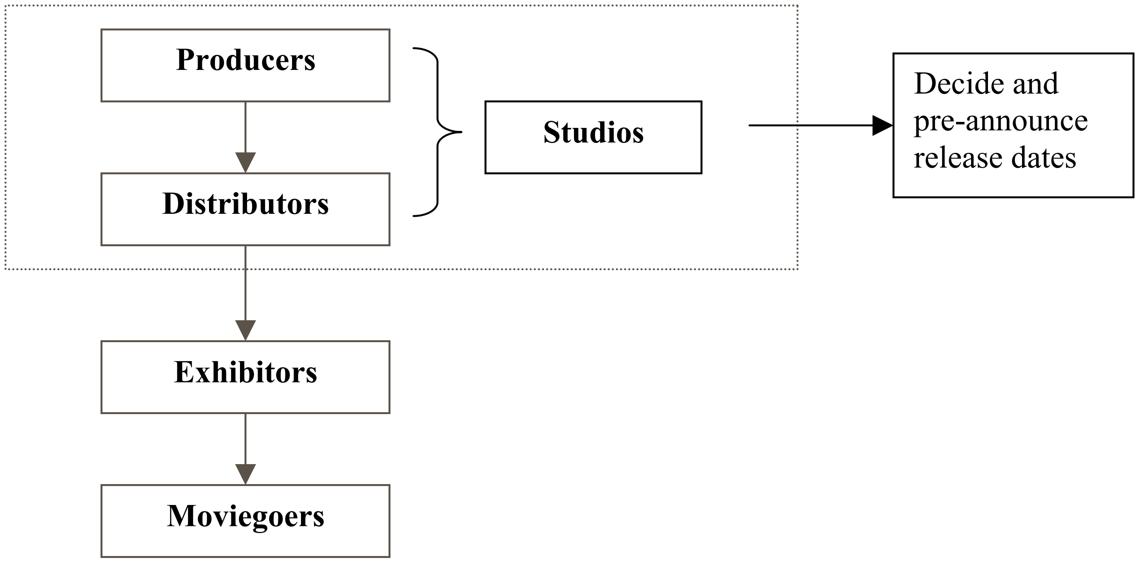


Figure 2. Seasonality in the Motion Picture Industry:
This figure illustrates the industry seasonality in the per capita movie ticket sales (the industry's weekly box office revenues divided by average ticket price and by the U. S. population) in the motion picture industry. (Source: Einav 2002).
Several holiday weekends, as illustrated in the graph, represent the highest per capita ticket sales.

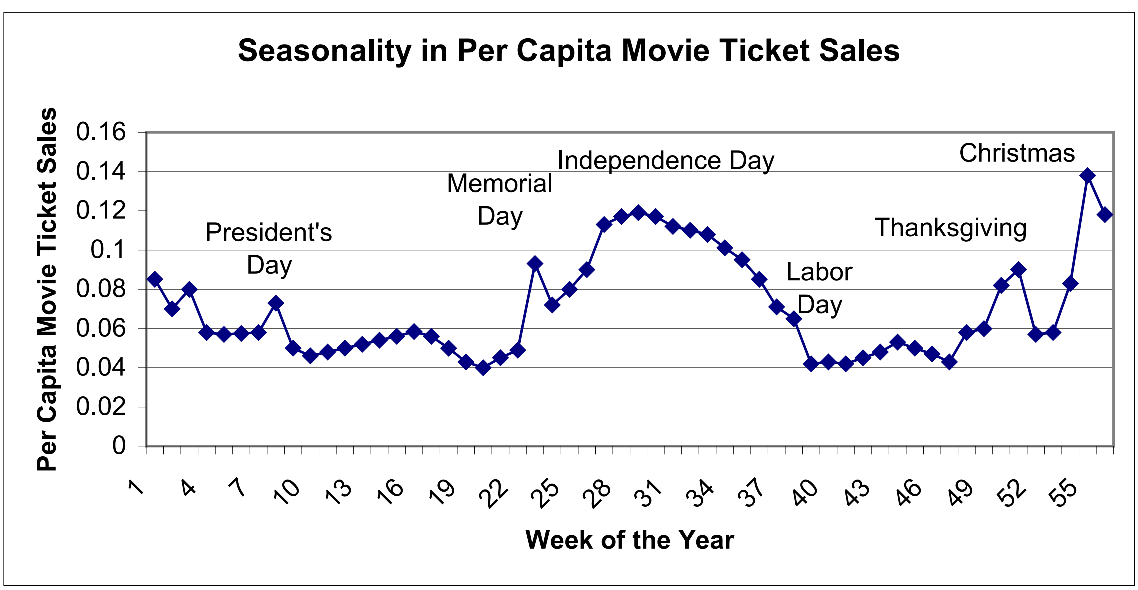
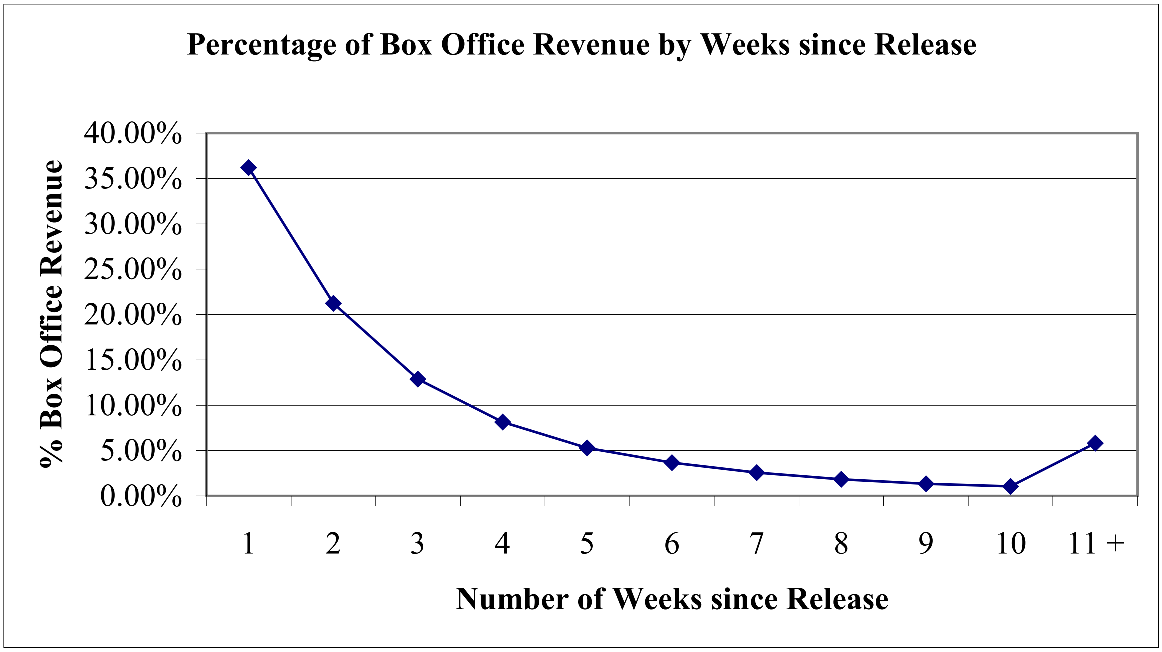


Figure 3. Short product life cycle in the motion picture industry

These two graphs illustrate the weekly percentages and weekly cumulative percentages, respectively, of the total box office revenues over a typical movie's product life cycle. These percentages are averaged across all movies in our EDI box office data sample.



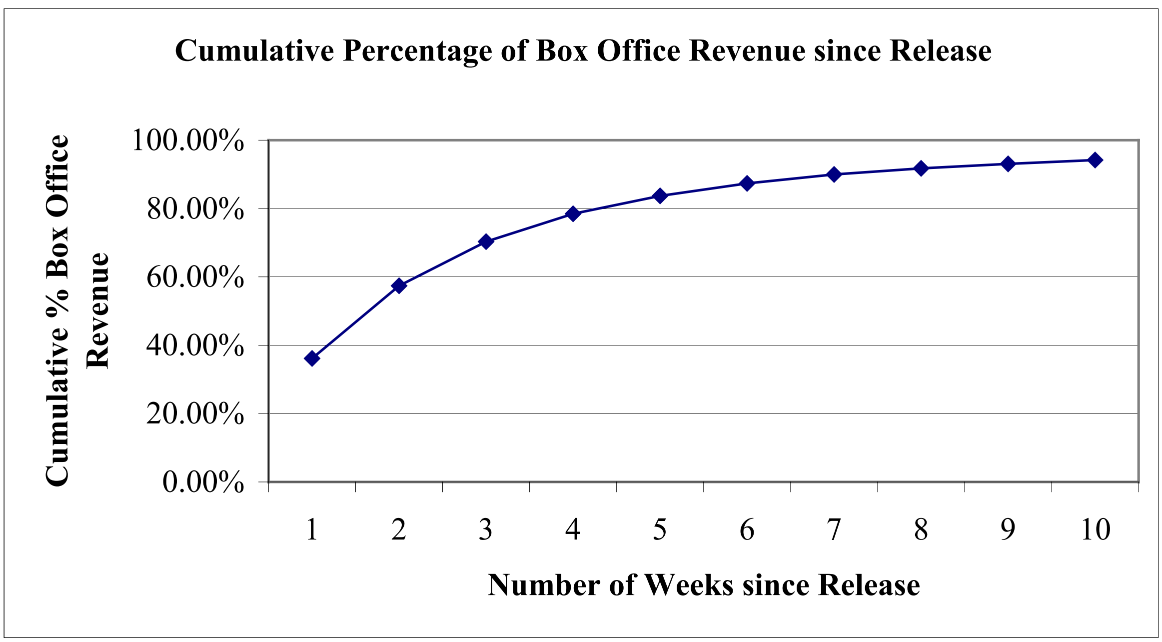


Figure 4. Studio and exhibitor activities for a typical movie

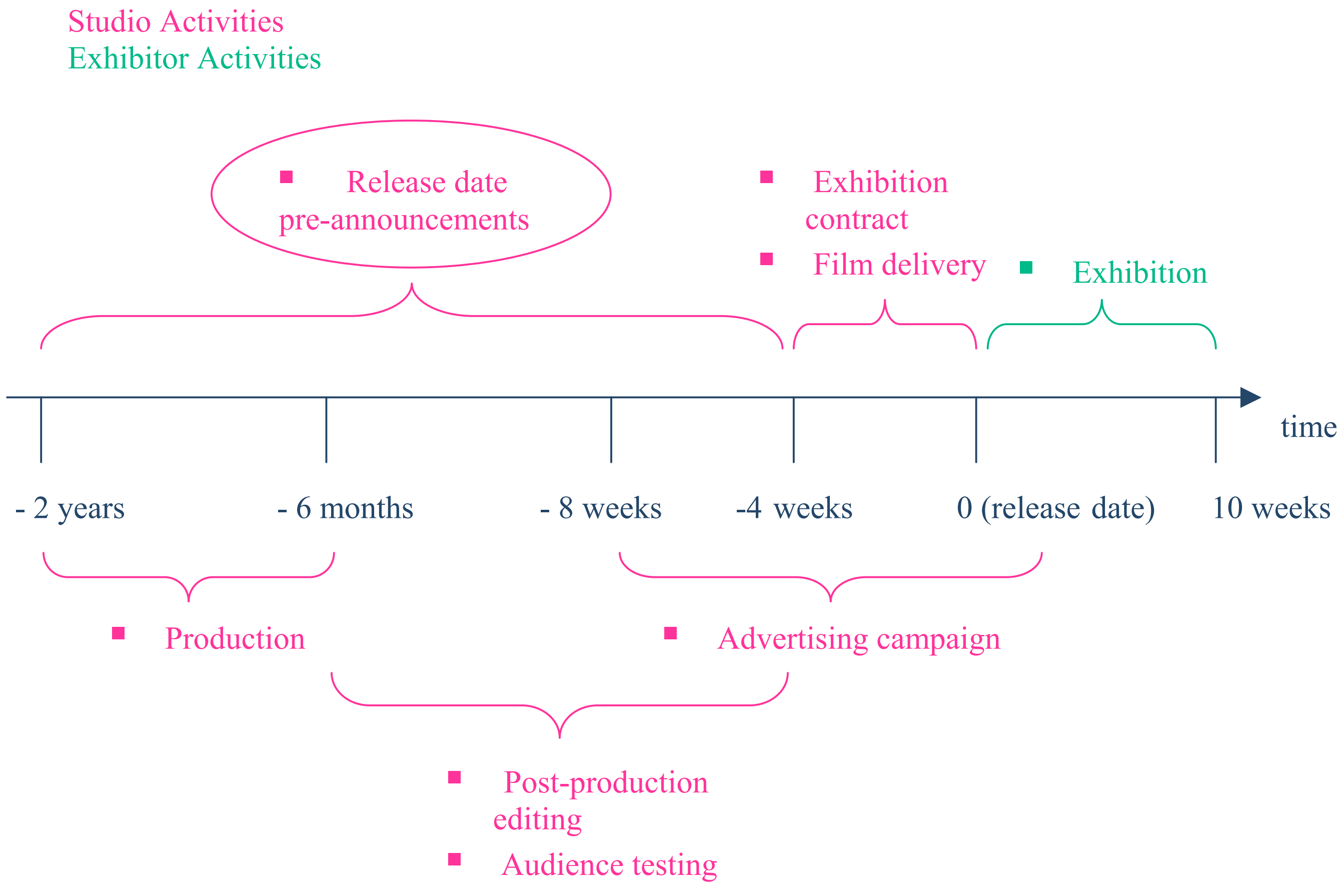


Figure 5. Timing of initial pre-announcements

Figure 5A.
This graph shows the distribution of the movies in our selected data sample by the timing of the initial pre-announcements defined as the differences in months between the time of initial pre-announcements (or the publication date of the initial pre-announcements) and the pre-announced release dates.

The mean is 5.81 months with the standard deviation of 2.65 months. The minimum and maximum is, respectively, 0.5 and 19 months.

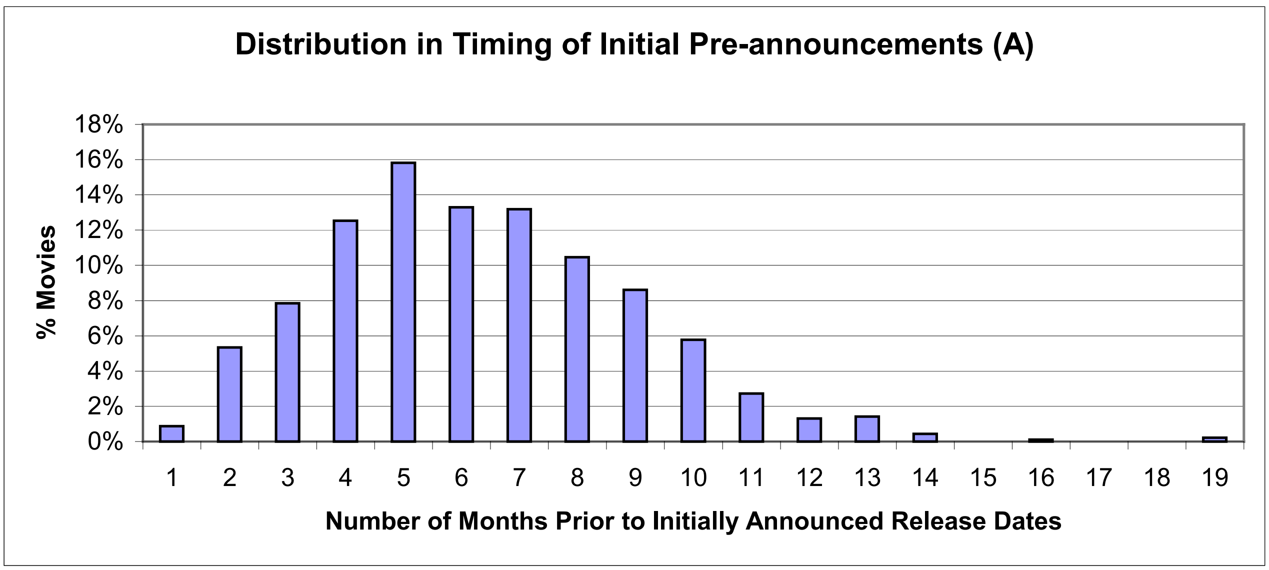


Figure 5B.
This graph shows the distribution of the movies in our selected data sample by the timing of the initial pre-announcements defined as the differences in months between the time of initial pre-announcements (or the publication date of the initial pre-announcements) and actual release dates.

The mean is 7.74 months with the standard deviation of 4.17 months. The minimum and maximum is, respectively, 0.2 and 38.3 months.

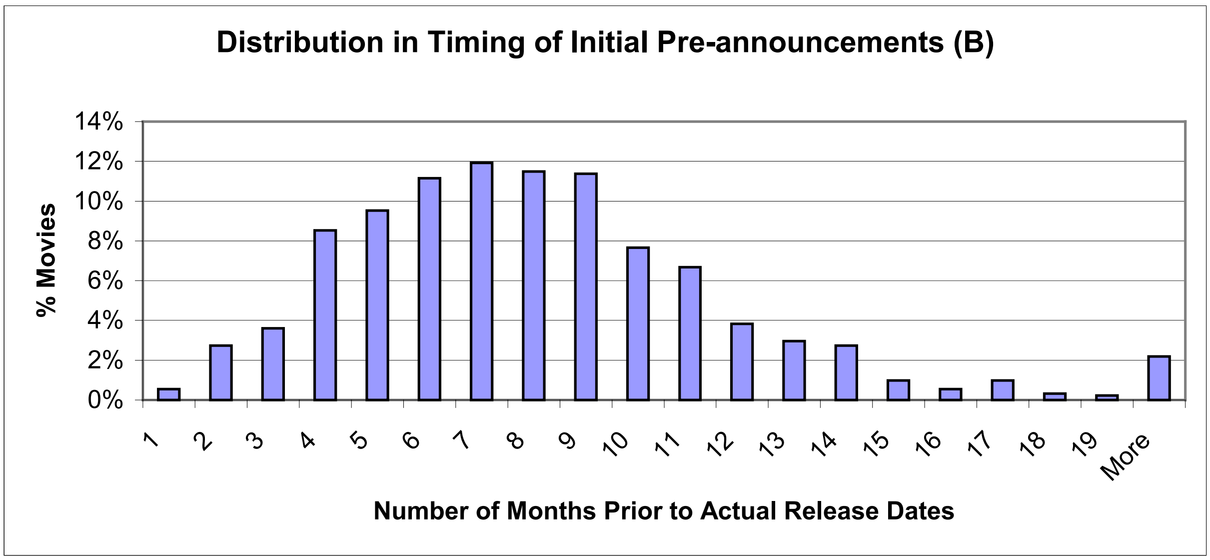


Figure 6. Frequencies of switches in the pre-announced release dates

This graph shows the distribution of the movies in our selected data sample by the number of times a movie has switched its targeted release date.
79% of the movies in our sample switched their announced release dates at least once.

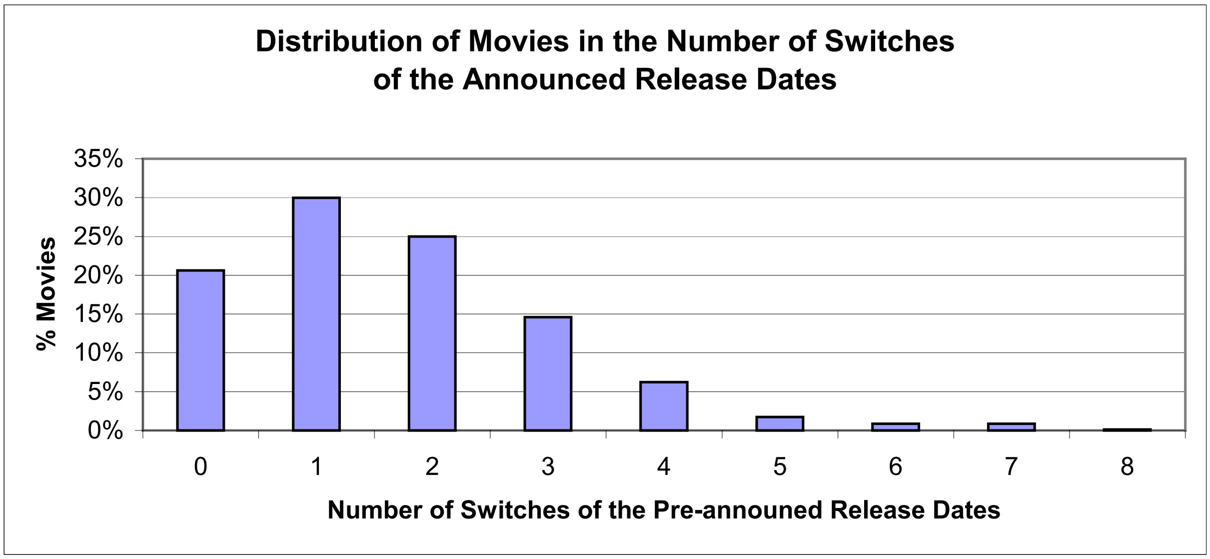


Figure 7. Magnitude of the switches of the pre-announced release dates

This graph shows the distribution of the pre-announcements by their differences in weeks (i.e., the magnitude of period-to-period switches) relative to the most recently announced release dates.

The majority of these differences are within the range of a few weeks.
84% of the pre-announcements represent no changes from the most recently announced release dates.

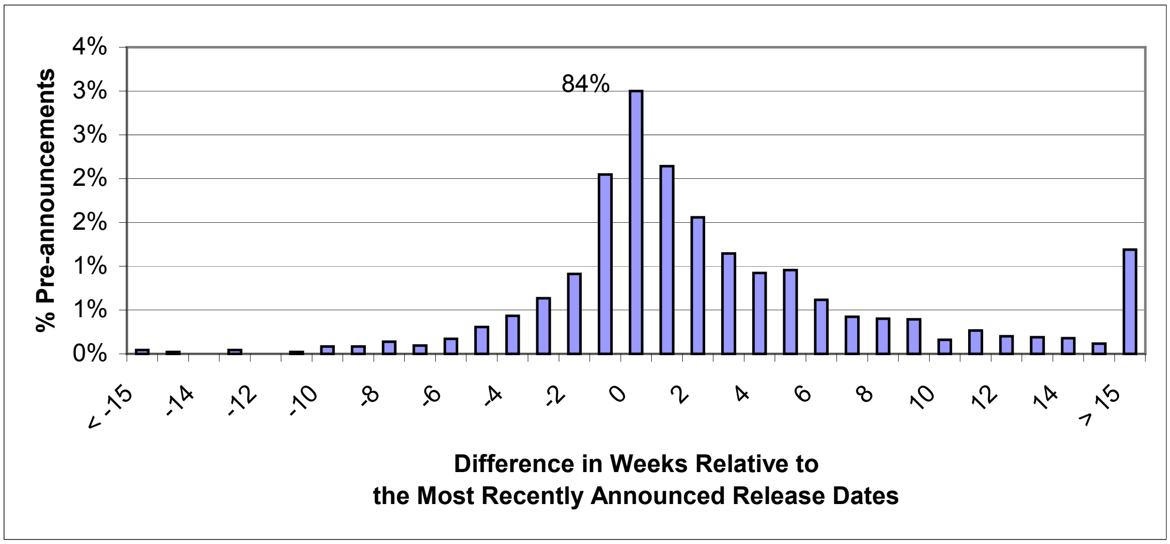


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Figure 8. The computational algorithm for the dynamic model

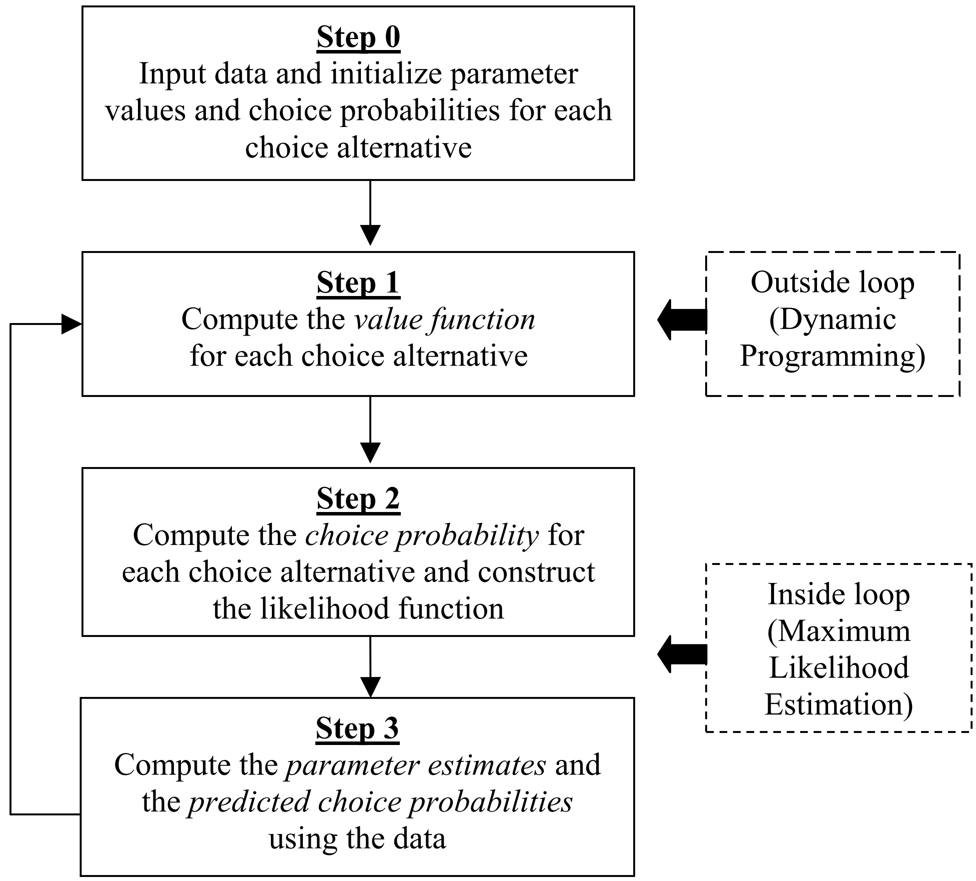

Figure 9. The computational algorithm for the static model