The Timing of Movie Releases:
Evidence from the Home Video Industry

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Abstract

In the movie industry, an intriguing question is why studios cluster their big theatrical hits during the Memorial Day or July 4th weekends in the early summer as opposed to the fall. This paper examines the home video industry to provide more evidence on whether booms in theatrical revenues are driven by the underlying seasonality of demand or the quality of movies released. First, I find no evidence of segmentation within the home video market by genre or newness of videos. Secondly, my estimates of the seasonality within the home video market suggest that Memorial Day and July 4th may be more favorable for a theatrical release than Labor Day.

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1 Introduction

During the July 4th weekend in 2003, the blockbuster films “Terminator 3” and “Legally Blonde 2” swept into theaters and elevated box office revenues for the top 10 films to $123 million. Eight weeks later on Labor Day, total box office revenues plummeted to $46 million as weaker titles such as “Dickie Roberts: Former Child Star” debuted in theaters. In general, studios often release blockbusters on the week of July 4th and mediocre films later on Labor Day. Conventional wisdom has always maintained that studios respond to exogenous seasonal patterns in demand: more people attend theaters during the summer than early fall when the TV season premieres and school resumes. A series of recent papers by Einav (2002, 2003, 2004) investigates this view. Einav (2004) notes that the surge in theater revenues on July 4 could arise from a higher quality of movies released during this period and not from exogenous changes in demand. His estimates of the demand for movies in theaters indicate that underlying demand is “stable over the summer, with a sharp decrease after Labor Day.” Furthermore, he finds that although few movies are released on Labor Day, a higher underlying demand exists during this week than gross industry revenues would imply. An intriguing question is why studios cluster their big hits during the July 4th weekend. In this paper, I use data from the home video industry to provide more evidence on whether booms in theatrical revenues are driven by the underlying seasonality of demand or the quality of movies released and to investigate why firms might cluster their releases as they do.

A few potential explanations exist for the timing of releases. First of all, releasing a movie in theaters at the beginning of summer allows the movie to accumulate revenues during the whole summer, which has a higher demand as opposed to the fall season. Secondly, market segmentation could lessen the undesirability of having multiple big movies debut in the same weekend. For instance, the debut of the comedy "Legally Blonde 2" and the action film "Terminator 3" within the same weekend may not be as undesirable, since each film may cater to a different audience. A third explanation suggests that since a typical delay between a movie's theatrical and home video release is between 4 to 6 months, releasing a movie in theaters at the beginning of summer allows the movie to reach home video in time for the holiday season.

Using evidence from the home video industry, I examine the latter two explanations. First, I analyze substitution patterns in the demand for home videos, and I find that differences in genre do not mitigate the degree of business-stealing among big movies clustered in the same weekend. Estimating a nested logit model, I do not find any evidence that newer releases compete more intensely than old releases. If the preferences over movies in theaters resemble those over movies on home video, my results support the finding of no segmentation within the theatrical market (Einav, 2002).

Secondly, I apply the estimates of the underlying seasonality in demand for rentals and sales in the home video market, and I investigate whether these seasonal patterns in the home video market impact a studio's incentive to release a movie. For most major films, a studio initially releases the movie into theaters, and then several months later, it releases the movie onto home video for rental or sale to consumers. The video release date plays a crucial role in a studio's profitability. Studios currently derive at least two-thirds of their revenues from the sales or rentals of feature films; since 1986, domestic wholesale gross revenues from home video have exceeded theatrical sources, and the first three weeks of a video's release generates approximately 50% of total rental revenues over a five month period.

The seasonality of the home video market implies that Memorial Day or July 4th may be a more favorable week for theatrical release than Labor Day. The underlying demand for videos surges in November and December due to holiday gift-giving, and the long-term relationship between theaters and studios pressures studios to not stray too far from a six month delay between theatrical and video release dates. My empirical results suggest that a movie which debuts in theaters in the early summer can appear in the home video market six months later around December and capitalize on the holiday gift-giving season. On the other hand, a movie that appears in theaters on Labor Day in September must delay its home video release to February of the next year.

Previous work on the home video market model rental revenues as solely a function of a movie's own characteristics. Frank (1994) derives the optimal timing of movie releases into the home video market; he looks at the opportunity costs of an early release of German movies into home video. He models the revenues earned in the theatrical and video markets as a function of time and does not explicitly allow for competitive effects across different movies. Lehmann and Weinberg (2000) consider a sample of 35 movies released onto video during 1994-1995, and they focus on the studio's decision of when to release a movie onto video following the theatrical run. However, their analysis does not explicitly control for changes in market size and competition over the weeks of the year. Waterman and Lee (2003) examine a set of videos released during 1988-1997. They find that a movie's own characteristics explain very little of the variation in the time between a movie's theatrical and home video release dates.

This paper also relates to the work of Seim (2005) on the effects of demand and competition in geographic space. While Seim analyzes the entry and location decision of video retailers in geographic areas, I examine how these factors influence concentration in time.

I begin with an overview of the home video industry. Then I estimate the demand for videos by constructing a dataset of 653 theatrical films that were released onto home video during 1999 to 2003, and I analyze the substitution patterns across genres and new releases and the seasonal pattern in underlying demand in the home video industry. Finally, I consider the relationship between the theatrical and home video release dates, and I pick a particular movie ("Shrek") that was highly successful at the box office and use it as an example to illustrate an upper bound for the potential losses in total home video revenues if the movie were released in theaters on Labor Day instead of Memorial Day. I also consider counterfactuals of how these losses vary with the "quality" (box office receipts) of the movie.

2 Industry and Data

The home video market has become increasingly important to studios over the last twenty years. In 1980, theatrical revenues in the U.S. comprised 30% of all industry revenues while home video accounted for 7%. By 2000, home video revenues had become the dominant source of income for the industry; nearly 40% of total industry revenues accrued from home video revenues, swamping the 15% contribution of theatrical revenues domestically.[1] With the advent of the DVD format, the home video market has continued to outpace revenues from theatrical exhibition. Currently, revenues from home video total more than $16 billion, and studios procure at least two-thirds of these revenues from sales or rentals of feature films.

Studios distribute movie videos on two different formats, VHS and DVD, which retailers can offer for rental or sale to customers.[2] In the past, studios have indirectly influenced a retailer's rent-versus-buy decision by charging a flat fee and manipulating the unit price charged

[1] The rest of a studio's revenue is comprised of revenues from foreign theatrical markets, pay cable, network TV, syndication, foreign TV, and made for TV films. The combined foreign theatrical market is approximately the same size as the domestic market. Studios rely on the domestic theatrical and home video markets as their largest revenue source.

[2] By law, studios cannot compel retailers to provide videos specifically for rental or for sale (also termed "sell-through"). The First Sale Doctrine of the Copyright Act of 1976 stipulates that the owner of the first copy of a video can dispense with it as he/she chooses without "further obligation or compensation to the original seller".

per video. Studios offered the video at two price points: a high rental price and a lower sell-through price to encourage retailers to purchase more copies and to offer them for sale to consumers (Mortimer, 2006b).[3] Since 1996, revenue sharing has become a fairly common practice for VHS. Instead of a fixed price per unit, the studio charges a nominal upfront fee of $0 to $8, and the retailer agrees to share a certain percentage of its rental revenues with the studio (Mortimer, 2006a).[4]

During my sample period 1999-2003, studios provide revenue sharing only for VHS format, and according to an industry source, about 80% of all VHS tapes that are not priced for sell-through are revenue shared; studios sell nearly all their DVDs at a sell-through price to retailers. On the street date of the video, retailers offer copies of the title on VHS and DVD for rental and sale. The sell-through market has become increasingly important in recent years. From 1999 to 2001, total revenues from video rentals remained stable around $8 billion whereas revenues from sales rose from $6 to $10 billion.

The release date of a video is crucial to the studios because a video accumulates the bulk of its revenues in the first few weeks of its release. According to weekly rental revenue estimates from Video Store Magazine Charts, approximately 50% of the rental revenues over a five month period are earned in the first 3 weeks. Studios do not compete intensely on the prices of videos, but instead they primarily compete in release strategies. Some major retailers, such as Blockbuster, offer a tiered pricing system for rentals where newer or more popular releases are

[3] For instance, a lower sell-through price of $20 per video encouraged retailers to purchase more copies and to offer them for sale to consumers. The studios could set a higher rental price of $60 to $75 per video with the intention that the retailer would earn revenues from several rentals for each video.

[4] Typically, the retailer shares 40 to 60% of rental revenues during the first few weeks of release with the studio; over a 26-week period, the percentage shared declines to zero. Afterwards the retailer may sell the rental tape to consumers as a "previously viewed" video.

more expensive. In general, the rental price of a video does not vary substantially by video characteristics such as genre or studio.

I construct datasets for rentals and sales in the home video market using data from Alexander and Associates (AA) consumer surveys. The dataset contains the quantities of VHS and DVDs rented and sold for a given title in each week from January 2000 to December 2003. Each week approximately 1,000 households were selected and interviewed. The survey procedure used stratified random sampling to create a balanced sample of 3-digit telephone exchanges across the U.S., and within each exchange, respondents were chosen on a random-digit dialing method to be representative of the geographical, age, gender, and ethnic composition of the U.S. population. The data from the telephone responses were aggregated to obtain estimates of national weekly rentals and sales for a given video title. See Chiou (2006) for additional details and summary statistics from the survey.

I collected additional information from the Internet Movie Database and Adams Media Research Titles Database. Internet Movie Database (IMDB) provides information on the characteristics of a movie including genre classification, MPAA rating (e.g., G, PG, PG-13, R), budget, and Academy Awards received. It also details the theatrical opening date, weekly number of screens during the theatrical run, and total gross box office of each movie. The Adams Media Research (AMR) Titles List Database contains all theatrical films released onto video during 1996 to 2002. It includes the home video distributor, running time, and suggested retail price for each movie.

To obtain a list of theatrical films that are released onto home video, I exclude videos of re-released movies, direct-to-video movies, and TV series from the sample. I also restrict my sample to videos that have been in release for fewer than 6 months. Similar to Einav (2004), I eliminate movies that did not reach wide release (a screening of 600 screens) at any point during their theatrical run; according to Einav (2004), these small movies most likely comprise a different segment of the industry. I also restrict my sample to theatrical titles that appeared at any point in the Video Store Magazine's (VSM) Top 50 Rental charts during 2000 to 2003. VSM ranks each title according to the combined rental revenues for VHS and DVD formats.[5] In the Alexander and Associates dataset, these top 50 videos comprise approximately 62% of all rental units sold and 47% of all sell-through units sold of theatrical films on average in a given week. Other older videos represent "catalog" titles that form a different niche of the industry.

My final sample contains 653 theatrical films. A video appears in the rental and sell-through samples for nearly 5 months on average with a standard deviation of 6 weeks. The final sample contains movies of varying theatrical success with box office revenues that range anywhere from $1 million to $400 million. The weekly rental units sold in the Alexander and Associates dataset ranges from 0.02 million to 6.31 million; the weekly sales units sold range from 0.008 million to 5.14 million.

3 Demand Estimation

The two potential explanations for the timing of movie releases rely on evidence from consumers' substitution patterns across different genres of videos and the underlying seasonality in market size for home videos. In order to quantify these effects, I estimate the weekly demand for video rentals and sales, and I inspect the degree of business-stealing across videos and how the underlying market size changes over the year.

[5] Video Store Magazine also reports the weekly combined rentals for VHS and DVD formats. I obtain similar qualitative results when my analysis uses these data (with a linear interpolation of rentals prices reported by Adams Media Research over the sample years September 5, 1999 to December 21, 2003).

3.1 Nested Logit Model

I specify a general form for a nested logit model of demand to model a consumer's choice of a movie within the rental and sales markets. A consumer's utility from choosing a given video is a function of the video's characteristics. I apply a four-level nested logit model by grouping all movies into an inside nest and then partitioning the movies into mutually exclusive sets by genre; within each genre, I partition the videos by newness into "newly released" and "old" videos. The outside good consists of all other leisure activities the individual could have chosen. The utility of individual *i* for choosing movie *j* in week *t* is expressed as:

$$u_{ijt} = \delta_{jt} + \nu_{ijt}$$

where δ_{ijt} is the mean utility and ν_{ijt} is an idiosyncratic individual error term. At any given week, only videos that were released less than 6 months ago (and that appear in the VSM Top 50 Charts at any point during 2000-2003) lie in the individual's choice set; the composition of videos in the choice set changes from week to week.[6] I normalize the utility of all consumers from the outside good (good 0) to be zero. The unobservable error term ν is distributed Type I Extreme Value and is correlated across videos within the same nests.

I specify the mean utility for choosing movie *j* in week *t* as:

$$\delta_{jt} = \gamma b_j + \tau_t - \lambda(t - r_j) + \alpha w_j + \xi_{jt}$$

where b_j is the log of the total gross box office revenues during movie *j*'s entire theatrical run, r_j is the video release week of movie *j*, τ_t is the underlying seasonal effect in demand for the inside

[6] This is a model of individual (per-capita) demand. The model assumes that each individual chooses at most one video per week. While a given household may view multiple videos in a given week, I assume that each member of the household engages in the choice decision and chooses at most one video per week. This is consistent with the dataset used in Chiou (2006); if we divide the weekly number of transactions in a given household by the household size (number of members), the average weekly number of DVDs purchased by an individual is approximately 0.47 with 97% of households purchasing at most 1 DVD per member. See Chiou (2006) for more details.

good, w_j is the window (i.e., the number of weeks between theatrical and video release dates). The mean utility depends on the quality of movie j as captured by its box office receipts, the decay effect (the number of weeks that have passed since the movie was released on video), the underlying seasonal effect in demand, and the delay of release of the movie onto video. The decay effect can either capture a preference by consumers for newness or the fact that consumers have already seen the video.

Following McFadden (1981), the choice probabilities of the nested logit model can be expressed in terms of the coefficients π_1, π_2, and π_3 on the inclusive values for each nest.[7] (See Appendix for formulas.) The parameters π_1, π_2, and π_3 represent the degree of substitution among alternatives in the genre-newness, genre, and inside nests. For instance, when the coefficient π_1 equals one, no correlation exists among tastes for alternatives in the same genre-newness nest; as the coefficient approaches zero, all individuals agree on the most preferred videos in the nest. If all the coefficients on the inclusive values equal one, then the model reduces to a standard logit. The nested logit model is consistent with random utility maximization for any set of values of the data if the coefficients π_1, π_2, and π_3 all lie between 0 and 1 (McFadden, 1981).

The model assumes that the decay effect is independent of the video release date and the window and is identical across all movies. The specification of the mean utility is similar to Einav (2004) for the demand for movies in theaters. However, instead of estimating a movie fixed effect, I use a movie's total box office revenues as a measure of quality. Given that window lengths typically range from 3 to 12 months, a movie will compete with nearly the same set of movies in the theatrical as well as home video market, so cumulative box office receipts reflects the quality of a movie relative to its competitors. I also incorporate the window length as an

[7] The nested logit model can also be expressed as a variance decomposition of the error term. See Cardell (1997).

additional term to capture any preference of consumers for a shorter delay between theatrical and video release dates.

The properties of the nested logit include independence of irrelevant alternatives within nests. The ratio of the market shares of any two new family movies is independent of characteristics of any other family or non-family movie. The independence of irrelevant nests constrains the substitution patterns across nests. For instance, if a new action movie is introduced, proportional substitution occurs from new family and old family movies, and disproportional substitution occurs from new action and old action movies.

Following Berry (1994), I invert the market share formula to find the mean utility and simplify to obtain a relationship between a movie's market share and the characteristics of the market and competition:

$$\ln s_{jt} - \ln s_{0t} = \gamma b_j + \tau_t - \lambda(t - r_j) + \alpha w_j + (1 - \pi_1\pi_2\pi_3)\ln s_{j|g} + (1 - \pi_2\pi_3)\ln s_{g|u} + (1 - \pi_3)\ln s_{u|IN} + \xi_{jt}$$

where $s_{j|g}$ = market share of movie *j* as a fraction of the market share of all movies in group *g*, $s_{g|u}$ = market share of group *g* as a fraction of the market share of group *u*, and $s_{u|IN}$ = market share of group *u* as a fraction of the market share of the inside nest.

3.2 Two-stage Least Squares Estimation of Demand

Using two-stage least squares, I estimate the equation above for two separate datasets: AA rentals and AA sell-through. I also consider an additional specification with a non-linear decay of utility by including a quadratic decay term. The within-group shares $s_{j|g}$, $s_{g|u}$, and $s_{u|w}$ are endogenous, since they depend on unobservable product-time characteristics ξ_{jt}. Berry (1994) suggests using the characteristics of other products in the nests as instruments, and Berry, Levinsohn, and Pakes (1995) use the sums of characteristics of other products as instruments for their mixed logit model. Accordingly, I use the sum of the characteristics of other movies in the group as instruments for the within-group shares.

For example, consider the movie "Shrek" as a newly released family video. To instrument for the market share of "Shrek" among new family videos $ln(s_{j|g})$, I examine the characteristics of all its rivals within the group – i.e., all other new family videos. I use two instruments: the sum of the log box office of all other new family videos and the sum of the number of weeks that all other new family videos have been in release.[8] This total log box office and total decay are used to capture the intensity of competition from rival videos. Movies that face rivals which are higher quality (higher total log box office) will tend to have lower within-group market shares, and movies that face rivals which are relatively new releases (lower total decay) will tend to have lower market shares. To instrument for the market share of all new family videos among family videos $ln(s_{g|u})$, I use two variables: the total decay and total log box office of all old family videos. Finally, I use two variables: the total decay and total log box office of videos from all other genres to instrument for the market share of family videos among all inside goods (all videos). For nests that contain only one movie, the within-group shares are mechanically equal to one.[9]

I calculate the market shares of movie j in week t by dividing movie j's quantity by the U.S. population in week t. A market share of 0.10 indicates that 10% of the population rented a video in a given week. I created a weekly population series by linearly interpolating annual population estimates from the U.S. Census Bureau.[10] Since the major holidays fall on different

[8] The estimated seasonal patterns are similar when I use the number of other videos in a nest as an instrument instead of total log box office and total decay. The coefficients of the inclusive values are estimated imprecisely due to a weaker first stage.

[9] By definition, the instruments are equal to zero when there is only one video in a nest.

[10] Since I assume that population increased linearly throughout the year, estimated population figures will be larger towards the latter part of the year. If population does not increase over the year, I would underestimate each movie's

weeks of the year from year to year, I inserted some "fake" weeks to re-scale the year so that all holidays fall on the same week across all years (1999-2003). Without this scaling, I may fail to capture changes in underlying market size associated with specific holiday weekends; this generates a total of 56 weeks in a year (Einav, 2004).

I define videos that are no more than two weeks old (t - r_j = 0 or 1) as "new", since common industry perception maintains that the popularity of a video falls dramatically after first two weeks of its release. My results are not sensitive to alternative definitions of newness (i.e., released this past week, released within the past three weeks) or if I allow decay to vary by season. For genre classification, I use information from the IMDB database which lists up to six different genre classifications for most movies.[11] For example, IMDB classifies "Shrek" as both a comedy and family movie. I initially assign each movie to its first genre classification. Then I group similar IMDB genres into broader categories by combining the action, adventure, and fantasy categories and by combining crime, thriller, and mystery movies under the label of suspense.[12] Comedies represent the most popular category and account for nearly a third of all movies. The horror category contains the fewest number of titles (40 movies) and only represent 6% of movies in the sample.

For the 2SLS regression, I cluster the standard errors at the movie level to take into account any serial correlation in revenues across weeks. I include a constant term in my

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weekly share towards the end of the year; this would work against finding a result of higher underlying demand in the holiday season.

[11] I obtain similar results when I use genre classifications from the Variety Weekly Box Office Charts. For about 30 out of 620 movies in such small categories as Western, Musical, or Science Fiction with no corresponding genre nest, I used the secondary classification from IMDB.

[12] The western, romance, and science fiction categories encompassed only a handful of movies in my sample, so I re-categorized each of these movies under its secondary genre classification. "Real Cancun" was the only video listed as a Documentary with no alternative genres, and I re-classified this as a Drama. In particular, most romance movies were either of the romance-comedy format or romance-drama format, and only one western movie and a handful of science fiction movies appeared in sample. The family category includes all films that appeal to both children and non-children audiences; that is, I included movies in the family category if they were listed as a family or animated movie under any of their alternative IMDB classifications.

regression and omit the dummy variable for the first week of the year, and I also include genre dummies.

3.3 Substitution Patterns and Underlying Seasonality

Figure 1 graphs the actual share of all rentals and sales separately. The industry share for rentals fluctuates more during the year and exhibits a high period in the summer and holiday seasons. In contrast, the sell-through market remains relatively stable for most of the year with a large surge in sales during the holiday season from Thanksgiving to early January. Since retailers offer most videos both for sale and rental on the day of its release, the different patterns in revenues suggest that the underlying seasonality may differ across the sales and rental markets. I will now estimate the seasonality in the sell-through market by specifying a model of demand for sell-through videos.

The estimated utility parameters reveal consumers' substitution patterns across different types of videos and fluctuations in the underlying market demand for videos over the weeks of a year. For the rental market, Table 1 displays the estimated coefficients for the box office, decay, window length, and genre dummies for the nested logit model along with the inclusive coefficients for each nest. Table 2 reports the corresponding coefficients for the sell-through market. In both tables, Column (3) reports the OLS estimates, and Columns (4) to (5) report the first-stage regression for each of the endogenous variables.

In Tables 1 and 2, the first-stage regressions have a good fit, and the relationship between the endogenous variables and corresponding instruments is in the expected direction and statistically significant. When the quality of rivals in the group rises (higher total log box office), a movie's within-group share falls; when the age of a movie's rivals increases (higher total decay), its within-group share rises.

As expected, the coefficient on the log of box office is highly significant and positive. Consumers enjoy higher utility from movies with higher "quality" as measured by box office revenues. The effect of quality has a stronger impact in the sales than the rental market. For every one percent increase in box office revenues, the market share of a movie relative to the outside good increases by 0.18% and 0.40% in the rentals and sales markets.

The coefficient on the decay term is highly significant and negative for both markets. Under the specification with a linear decay, Column (2) of Tables 1 and 2 indicate that a movie experiences a 2.4% decline in market share relative to the outside good for each week of its release.[13] Individuals derive less utility from an older video which could indicate a preference for "newness" or that they have already rented the movie in previous weeks. The decay for movies on home video has a smaller magnitude than the decay for movies in theaters (22%) as estimated by Einav (2004).[14]

I would expect the coefficient on window length to be negative, since consumers may receive less utility from videos with longer windows due to impatience or a preference for watching movies that not too "old" relative to the theatrical release date. This variable is potentially endogenous if higher quality movies have a longer window; the regression however controls for quality through the box office measure. The estimated coefficient is negative and statistically significant.

[13] Interacting the decay coefficient with genre, blockbuster, or year dummies does not affect the qualitative results of the demand estimation. I define a blockbuster as a movie with cumulative (domestic) box office revenues that exceed $100 million.
[14] Results using the rental dataset from Video Store Magazine have a higher decay of 11%, but still lower than the estimate for movies in theaters.

Recall, the inclusive coefficient represents the degree of business-stealing among movies within a given nest, and it lies between 0 and 1. An inclusive coefficient of 1 indicates that an individual's idiosyncratic shocks are independent across movies within the nest, and a inclusive coefficient of 0 indicates that all individuals agree on the "best" movie within a nest. The inclusive coefficients must lie between 0 and 1 to be consistent with random utility maximization; in the estimating equation, this is equivalent to the condition that the coefficients on these within-group shares lie between 0 and 1, and the coefficient on $ln(s_{j|g})$ is greater than or equal to the coefficient on $ln(s_{g|u})$, and the coefficient on $ln(s_{g|u})$ is greater than or equal to the coefficient on $ln(s_{u|IN})$ (McFadden, 1981).

The demand estimation results are consistent with the conditions for utility maximization. In Table 1, the coefficients on the within-group shares are approximately equal; for the rental market, π_3 = 0.3, and $\pi_1 = \pi_2$ =1. In Table 2, although the point estimates for the within-group shares differ, I cannot reject the hypothesis that all three coefficients are equal when I allow for nonlinear decay (p-value = 0.69); in the sell-through market, π_3 = 0.7, and $\pi_1 = \pi_2$ = 1. Less crowding out occurs in the sales than rental markets, since the inclusive coefficient for the inside nest in the sales market (0.7) is greater than the rental market (0.3).

I do not find any evidence of segmentation in either the sales or rental markets. Nesting by the inside good matters (π_3<1), but nesting by genre or newness does not matter ($\pi_1 = \pi_2 = 1$). In effect, the 4-Level nesting structure can be collapsed to a 2-Level structure that nests only inside alternatives. This conclusion is consistent with Einav (2004) which finds that nesting by the inside good matters for theatrical releases. Business-stealing effects are not stronger among rentals of the same genre or newness. When a new video is introduced, the share of all rentals declines proportionately more than the share of the outside good. However, the introduction of a video of a given genre (or newness) does not lead to a proportionately larger decline in the share of videos of the same genre (or newness). For instance, the introduction of an action movie in a given week does not lead to a proportionately larger decline in the share of action movies compared to other genres.

Figure 2 depicts the underlying seasonality in the rental and sell-through markets by graphing the estimated weekly coefficients. Since I omitted the dummy variable for week 1 and included a constant term in the regression, the reported coefficient for week t (where t = 2,...,56) represents the market size of week t relative to week 1. The rental market faces a relatively high demand period in the early months of the year as the winter weather encourages people to seek leisure activities indoors. The summer season also experiences a high underlying demand with the onset of school vacations and re-runs of television shows. In the fall, the market size declines by 20% to 30% most likely due to the beginning of the school year and the premiere of a new season of television shows. Once Thanksgiving arrives, the market size begins to expand, since the opportunity cost of leisure falls during the holiday season from Thanksgiving to Christmas.

The seasonal pattern for rental videos shares some similarities to the seasonality for movies in theaters (Einav, 2004). The early months of the year and the summer season retain a high underlying market size, and market size starts to decline after Labor Day as the year progresses through the fall season.

The sell-through market size remains relatively stable with the exception of the last quarter of the year. The underlying market size spikes during the last two months of the year, as consumers engage in holiday shopping. The market size for sell-through videos exhibits greater variation than rentals during the year. In Figure 2, the impact of market size on a video's share (relative to the outside good) differs by 40 percentage points between the weeks with the lowest and highest market size while for the sell-through market, the difference between the weeks with the lowest and highest market size is approximately 80 percentage points.[15]

Now that I have identified the seasonal underlying demand for videos, I will consider the second potential explanation for the timing of movie releases. In the next section, I discuss how this seasonal pattern, in conjunction with the long-term relationship between studios and exhibitors, provides incentives for a studio to release a movie into theaters during July as opposed to September.

4 Relationship between Theatrical and Home Video Markets

The second potential explanation rests on the idea that the choice of a theatrical release date is part of an overall movie timing game which includes the theatrical and home video markets. Studios set theatrical release dates in anticipation of revenues from the home video market. Since studios and theaters maintain a long-term relationship, the choice of a theatrical date has an implication for the theater-to-video window. First, I discuss the theater-to-video windows and the nature of the relationship between studios and theaters owners. Next, I explain the timing of movie releases and why an early summer release be a more attractive than Labor Day in light of the findings. I also examine the historical pattern of theatrical releases over these two holiday periods. To illustrate an upper bound to the potential losses in the home video market, I estimate the loss in home video revenues when the theatrical release of "Shrek" is delayed from Memorial Day to Labor Day. I also consider how these losses vary with the "quality" (box office) of the movie.

[15] When movie fixed effects are used instead of cumulative box office revenues, a similar seasonal pattern emerges for the rental market. In the sales market, the last four weeks of the year still exhibit a higher underlying demand; a 55 percentage points difference exists between the weeks of the lowest and highest market size. Although the estimated effect is smaller, these weekly coefficients as well as the other demand coefficients are imprecisely estimated.

4.1 Theater-to-Video Window

The key players in the timing of video releases include the studios (the distributors of the movie), movie theaters (exhibitors), and video retailers. The studios can be regarded as the distributors of the product, since they establish the theatrical and video release dates. The major studios are owned by 6 companies, which consist of the Walt Disney Company (Buena Vista, Touchstone Pictures, Miramax Films), Sony (Sony Pictures, Columbia TriStar), Viacom (Paramount), News Corporation (20th Century Fox), Time Warner (Warner Brothers, New Line, Castle Rock), and General Electric (Universal, Vivendi, USA Networks). These so-called "majors" produce, finance, and distribute their own movies as well as movies created by independent filmmakers. Consequently, each studio maintains a production unit that produces the films and a home video distribution arm that oversees the release of the movie onto home video. A handful of theater chains own 65% of the screens in the U.S. and collect at least 80% of total box office revenues domestically: United Artists and Regal, Loews Cineplex, AMC Entertainment, the GC Companies (General Cinema), Carmike Cinemas, Redstone, Cinemark USA, and Marcus Corporation.[16]

A timeline for a typical movie may proceed as follows. First, the studio decides when to release the movie into theaters. The theatrical run of a movie can range anywhere from one to four months. Then a period of about two months follows the theatrical run where the movie can only be seen in the travel industry in airlines or in hotel rooms. Then studios "float" around some potential street dates to video retailers, and after hearing the retailers' reactions and the potential release dates of other movies, the studio announces the date of the movie's home video release

[16] Vogel (2001)

(Waterman and Lee, 2003). Afterwards the movie makes its way through the remaining channels of distribution: pay-per-view, cable television, and network syndication.

The theater-to-video window is defined as the number of weeks between the theatrical and video release date of a movie. As shown in Figure 3, variation in window length exists anywhere from 3 to 12 months. However the majority of window lengths lie close to the mean of 5.5 months. In my sample of videos, studios released approximately 83% of movies within 4 to 7 months after the theatrical release. Less than 6% of movie had a window shorter than 4 months.[17] While this study focuses on the period 1999-2003, Waterman and Lee (2003) observe an earlier panel from 1988 to 1997, and they find that although variation in window lengths exist for individual movies, average video windows have consistently remained close to a six month industry "benchmark" over their period.[18]

Figure 3 also plots the histograms of the video release dates for movies released in theaters during the July and September (which includes Labor Day). Of all the movies released in theaters during the month of July, approximately half were released onto video during the peak holiday season, and about 50% of these movies were blockbusters (cumulative box office revenues greater than $100 million). For movies that debuted in theaters during September, only 18% of the movies were released onto video during the holiday season, and these films were primarily unsuccessful at the box office ($6 to $37 million with a mean of $17 million) and consequently had a short theatrical run. Figure 1 also depicts the histograms for movies that were

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[17] These patterns persist whether the theatrical release date is defined as the opening date of the movie, the date at which the movie accumulates a certain percentage of its (eventual) box office receipts (e.g., 85% of cumulative box office receipts), or the date at which the movie achieves a particular threshold number of exhibition screens.

[18] Waterman and Lee (2003) control for the movie's box office performance in their regression of window lengths. While trade groups such as the National Association of Theater Owners have argued that theater-to-video windows are decreasing (Sweeting, 2005), Hettrick (2005) suggests that smaller box office movies with short windows "misleading bring down the overall average" of window lengths. Note that any pattern in shrinking windows over the two decades is also consistent with the observed trend of the increasing importance of home video during this time period (Indvik, 2004). Long-term relationships with exhibitors can exert pressure on the extent to which the window shrinks.

released in July and had cumulative box office revenues less than $25 million. Even for these "low quality" movies, the video release was not delayed until January of the next year; the majority of these movies were released in October and November.

4.2 Pressure on Window Lengths

The preceding section provided evidence that the majority of window lengths lie within a narrow range of 4 to 7 months. As the executive vice president of marketing and sales for Fox Home Entertainment, Mike Dunn stated that "the window for Fox is a routine six months, but we pick the date based on seasonality. There can be some (flexibility) based on seasonality or holiday periods and where the title should go in terms of (competition at the time)." The institutional features and the repeated nature of the game exert pressure on the upper and lower bounds of window lengths.

Studios do not want to set windows that are too short. In the U.S., no legislation exists on the windows a distributor can set, and contracts between studios and theater owners do not explicitly set a window for a movie (Waterman and Lee, 2003). However the long-term relationship between theater owners and studios exert pressure on window lengths. When Fox announced that it would release the movie "From Justin to Kelly" only six weeks after its theatrical opening in 2003, several major theater chains including Loews, Regal, and National Amusements voiced disapproval and threatened to not screen the movie at any of their theaters. Fox eventually relented and delayed the street date by three weeks to August 2003. From time to time, the National Theater Owners (NATO) also publish statements in the trade press that call for adherence to a 6 month window (Waterman and Lee, 2003). In general, studios express concern that short windows may lead a theater to “punish” the studios in the future by prematurely terminating the theatrical run of their less successful movies.

Sometimes a studio may publicly admonish another studio for releasing a movie with a particularly short window. In 1996, when Warner Brothers and Fox released “Twister” and “Independence Day” on video less than 5 months after theatrical openings, a Paramount executive declared publicly “What we don’t want is to have the consumer think they can pick up a movie on video in three months. It’s a very dangerous trend.”

On the other hand, studios do not want to set windows that are too long. Studios prefer to release a movie onto video not too long after the theatrical release, so they can capitalize on the “advertising blitz” that accompanies the theatrical release of a movie. The actors often embark on nationwide publicity tours and press junkets; the premiere night and trailers also generate a lot of advertising. If a studio waits too long after the theatrical opening to release the movie onto home video, it must invest in a substantial amount of advertising to remind consumers about the movie and re-stimulate interest in the film.

Often times, the box office receipts of the movie do not cover all the production costs of the movie. Particularly for the less successful movies, studios rely on revenues from the home video market to cover the costs. Industry-wide agreements and statutes or contracts in Europe with exhibitors explicitly recognize the importance of shorter windows for less successful films. For instance, in France legislation exists that prevent studios from releasing a movie onto home video until 12 months after the theatrical debut, but if total box office admissions for a movie lie below 100,000, then the minimum window is lowered to 6 months.

4.3 Explaining the Timing of Movie Releases

The pressure on window lengths imply that the relative attractiveness of releasing a movie into theater on Memorial Day compared to Labor Day will depend on whether the holiday effect in the home video market outweighs the "Labor Day effect" in the theatrical market. Given the relative importance of the home video market, it is likely that the holiday effect will dominate. To look for historical evidence, I examine the pattern of movie releases into theaters over these two holidays.[19] My hypothesis is that as the home video market becomes relatively more attractive over time, the gap between the number and total box office of movies released in theaters around July 4th compared to Labor Day should increase over time as well. I collect data from the Weekly Box Office Charts on Variety.com, and I created a dataset of movies released in theaters from 1/11/1985 to 12/26/2003 during the first ten weeks of their run. I identify the July 4th and Labor Day weekends in the Variety dataset, and I compare the number and total box office of movies released within two weeks before and after these holiday weekends. I cleaned the data using the criteria from Einav (2004).[20]

A simple regression on the gap between total box office of movies near July 4th and Labor Day and a time trend shows a positive relationship. The coefficient is statistically significant and indicates that for every year, the gap in total box office between these two holidays increases by 12.5 million in 2003 dollars. The R-squared is 0.19. The results are similar when I take a window of one week within each holiday or if I look at the holiday weekends

[19] In principle, I can construct a timing game. This would imply a joint estimation of the theatrical and home video markets. The goal of this paper is to use evidence from the demand in the home video market to consider the seasonal pattern of theatrical releases. This evidence would be separate from any additional assumptions needed to model a structural timing game across two different markets.

[20] I restricted the sample to movies that reached a wide release at some point during their run; movies that do not reach this criteria are "relatively small movies, in a different segment of the industry". Similar to Einav (2004), I consider the actual release date to be the first week in which the number of screens is "high enough" (exceeds a maximum of 400 screens and 30% of eventual maximal number of screens showing the movie.) As a measure of total box office receipts, I take the sum of a movie's box office revenues during the first 10 weeks of its run, and due to the long panel, I use the CPI to deflate the box office revenues. I observe one data point for each year in the sample (1985 to 2002).

alone; however, the coefficients are not statistically significant. Similarly, there is a positive relationship over the sample period when I include a quadratic time trend as well; though the coefficients are not estimated precisely. While total box office is increasing over time, the number of movies is actually decreasing over this period. For every two years that passes, the gap between movies shown near July 4th and Labor Day decreases by one movie. Although fewer movies are being shown near July 4th relative to Labor Day, these movies are of higher quality.

To illustrate an upper bound for the potential losses from delaying a theatrical release date, I consider the particular example of the successful family movie "Shrek". Dreamworks released "Shrek" in theaters under a wide release on May 20, 2001 and onto home video on November 2. "Shrek" was highly successful in theaters, accumulating $260 million in box office revenues in the U.S. over 8 months.

First, I use the demand estimates and calculate the predicted market shares within the sales and rental markets from the actual video release date during the first 10 weeks of release. I calculate predicted quantities based on the U.S. population size, and I estimate total revenues using interpolated price data.[21] The rental prices are annual weighted averages from the Video Software Dealers Association, and I obtained average prices of sell-through DVDs and VHS from Adams Media Research.[22] Then I use a similar procedure to predict revenues, assuming that the Dreamworks released "Shrek" in theaters in the week of Labor Day and preserved the same theater-to-video window of 23 weeks. Table 3 contains estimates and standard errors of overall revenues in the rental and sell-through market.

[21] I assume that prices followed a linear relationship throughout the year. If prices for videos "step up" after Christmas, then my calculations give an upper bound on the gains from delaying a theatrical release.
[22] I use the proportion of DVD vs. VHS items in my sample to obtained weighted prices for the sell-through market.

In the sales market, predicted revenues drop from $90 million to $78 million for the first 10 weeks of the video's release. Rental revenues increase slightly by $3 million from $32 to $35 million; underlying demand for rentals is slightly higher in the early months of the year compared to the fourth quarter. As a result, delaying the theatrical release of "Shrek" to Labor Day results in a loss of $10 million in the home video market.

To see how the potential losses from delaying a theatrical release date varies with "quality" or box office success, I compute counterfactuals where I vary the box office receipts for "Shrek" from $50 million to $200 million.[23] Table 3 illustrates how the losses diminish for "smaller" movies.

5 Conclusion

Einav (2003, 2004) uncovers the empirical puzzle that across seasons, studios release their high quality movies during July 4th as opposed to Labor Day even though the estimated underlying demand remains "stable" throughout the summer. Within a given season, studios tend to over-cluster their releases on big holiday weekends.

This paper examines two potential explanations for the timing of movie releases using data on the home video market. First, I do not find evidence of market segmentation that would indicate that over-clustering measures do not take into account differences across genres. Secondly, the main positive finding is that a studio's choice of the theatrical release date may be part of an overall timing game between the theatrical and home video markets. Studios may set theatrical release dates in anticipation of the home video market. The underlying seasonality of

[23] In principle, an indirect effect also exists; theater box office revenues could vary with a different theatrical release date. Unfortunately, without the full panel of theatrical movies and the estimated movie fixed effects, I cannot compute these changes from the reported estimates in Einav (2004).

the home video market implies that theater-to-video windows lies within the range of 4 to 7 months. Consequently a theatrical release of July 4th may actually be a more favorable theatrical release date of Labor Day because then the movie can debut onto home video 5.5 months later in time for the holiday gift-giving season. While the seasonality of the home video market provides an explanation for the across-season puzzle, it does not account for the over-clustering on holidays that Einav (2003) also finds within seasons.

My explanation is complementary with an uncertainty argument for the within season puzzle. Einav (2003) posits that high uncertainty regarding the quality of a movie may make all movies appear identical ex ante; studios may tend to over-cluster on big holiday weekends given that all movies appear identical. The theatrical market faces a lot of uncertainty as the primary market. By the time a studio must set the video release date of a movie, it has already observed the movie during part of its theatrical run; the studio has a good indication of the movie's overall quality and how well the movie fared in the box office compared to its competitors.

A possible extension for future work involves exploring whether any learning occurs between the theatrical and home video markets. Do differences exist in video release strategies for movies that fail to meet their high box office expectations compared to those that do? Another avenue of interest is to consider the release pattern as the result of a timing game with multiple equilibria and to investigate how selection occurs among the different equilibria. For instance, are studios with blockbuster movies able to select the resulting equilibrium which is most favorable for them?

My results have implications more broadly for products with a sequential distribution channel or ancillary markets; seasonality in the secondary market of a low-margin product such as home video can affect product release decisions in the primary market of a higher-margin product such as theatrical exhibition. In certain markets such as cars, computers, and cameras, versions of products are initially released into a high-margin market before a broader and more lower-margin one (Moorthly and Png, 1992; Prasad et al., 2001). The implications of timing in sequential markets are relevant for media where products do not compete intensely in price, but rather in release dates. A close analogy to the movie industry is the publishing industry where publishers maintain a stable window of releasing paperback versions of their books approximately one year after their hardcover versions (Wilson and Norton 1989).

The timing of movie releases sheds insight on the importance of market segmentation and seasonal patterns in demand. It also emphasizes the significance of ancillary markets in influencing decisions in the primary market and of long-term relationships between firms.

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Appendix

Nested Logit Probability Choice Formulas

Following McFadden (1981), I express the choice probabilities of the nested logit model in terms of the coefficients on the inclusive values for each nest. The mean utility can be partitioned into variables common to each nest: $\delta_{jt} = \beta X_{jt} + \alpha Y_{gt} + \gamma Z_{ut} + \varphi W_{IN,t}$ where X contains variables specific to movie j (such as box office, decay, and window), Y contains variables common to all videos in the same genre-newness nest g as video j, Z contains variables common to all videos in the same genre u as video j (such as a genre dummy), and W contains variables common among all videos (such as the weekly dummy). Suppressing the time subscript for convenience, the probability of choosing video j is given by:

$$p_j = \frac{e^{\beta x_j/(\pi_1\pi_2\pi_3)}}{\sum_{k\in J_g} e^{\beta x_k/(\pi_1\pi_2\pi_3)}} \frac{e^{\alpha Y_g/(\pi_2\pi_3)+\pi_1 I_{1g}}}{\sum_{h\in C_u} e^{\alpha Y_h/(\pi_2\pi_3)+\pi_1 I_{1h}}} \frac{e^{\gamma Z_u/\pi_3+\pi_2 I_{2u}}}{\sum_{v\in IN} e^{\gamma Z_v/\pi_3+\pi_2 I_{2v}}} \frac{e^{\varphi W_{IN}+\pi_3 I_3}}{1+e^{\varphi W_{IN}+\pi_3 I_3}}$$

where $I_{1g} \equiv \log\left(\sum_{j\in J_g} e^{\beta x_j/(\pi_1\pi_2\pi_3)}\right)$, $I_{2u} \equiv \log\left(\sum_{g\in C_u} e^{\alpha Y_g/(\pi_2\pi_3)+\pi_1 I_{1g}}\right)$, and $I_3 \equiv \log\left(\sum_{u\in IN} e^{\gamma Z_u/\pi_3+\pi_2 I_{2u}}\right)$.

Video j belongs to genre-newness g, genre u, and the set of inside goods IN; J_g is the set of all videos in genre-newness g, C_u is the set of all videos in genre u, and IN is the set of all inside goods. The parameters π_1, π_2, and π_3 are the coefficients on the corresponding inclusive values I_1, I_2, and I_3 of the genre-newness, genre, and inside nests.

Table 1. Home Video Rentals

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	OLS	1st stage: $\ln(s_{j\|g})$	1st stage: $\ln(s_{g\|u})$	1st stage: $\ln(s_{u\|IN})$
LNboxoffice	0.183**	0.175**	0.005**	0.443**	0.046**	0.060**
	(0.024)	(0.022)	(0.002)	(0.008)	(0.003)	(0.004)
decay	-0.024**	-0.035**	-0.001**	-0.063**	0.001	-0.010**
	(0.003)	(0.005)	(0.0002)	(0.001)	(0.0005)	(0.001)
$decay^2$		0.0005**				
		(0.0001)				
window	-0.003*	-0.003*	0.0002	-0.009**	-0.001	0.001+
	(0.001)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)
$\ln(s_{j\|g})$	0.671**	0.683**	0.989**			
	(0.041)	(0.038)	(0.002)			
$\ln(s_{g\|u})$	0.665**	0.703**	0.989**			
	(0.041)	(0.035)	(0.003)			
$\ln(s_{u\|IN})$	0.675**	0.691**	0.991**			
	(0.042)	(0.038)	(0.003)			
Action	0.078**	0.072**	-0.0002	-0.012	0.017	0.256**
	(0.026)	(0.025)	(0.005)	(0.030)	(0.013)	(0.015)
Suspense	0.157**	0.149**	0.002	0.078*	0.042**	0.363**
	(0.029)	(0.028)	(0.006)	(0.031)	(0.013)	(0.015)
Comedy	0.094**	0.087**	0.003	-0.049	0.047**	0.296**
	(0.026)	(0.024)	(0.005)	(0.031)	(0.014)	(0.015)
Drama	0.129**	0.120**	0.001	-0.087**	0.043**	0.463**
	(0.028)	(0.026)	(0.005)	(0.030)	(0.013)	(0.014)
Horror	0.116**	0.112**	0.002	0.415**	0.061**	-0.141**
	(0.029)	(0.027)	(0.007)	(0.037)	(0.016)	(0.018)
To instrument $\ln(s_{j\|g})$:						
Total log box office				-0.063**	0.012**	0.041**
				(0.001)	(0.001)	(0.001)
Total decay				0.010**	-0.002**	-0.007**
				(0.0004)	(0.0002)	(0.0002)
To instrument $\ln(s_{g\|u})$:						
Total log box office				0.001	-0.053**	0.045**
				(0.002)	(0.001)	(0.001)
Total decay				0.002**	0.006**	-0.008**
				(0.001)	(0.0003)	(0.0003)
To instrument $\ln(s_{u\|IN})$:						
Total log box office				0.003**	0.0003	-0.011**
				(0.001)	(0.0004)	(0.0004)
Total decay				-0.001**	-0.0001	0.002**
				(0.0002)	(0.0001)	(0.0001)
Constant	-4.217**	-4.080**	-2.330**	-2.202**	-0.466**	-2.166**
	(0.249)	(0.222)	(0.017)	(0.111)	(0.048)	(0.054)
Observations	9927	9927	9927	9927	9927	9927
F-statistic				286.98	277.14	468.34
R-squared	0.93	0.94	0.98	0.67	0.66	0.77

Notes: Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%
The omitted genre is Family.
Video *j* belongs to genre-newness nest *g* and genre nest *u*.

Table 2. Home Video Sell-Through

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	OLS	1st stage: $\ln(s_{j\|g})$	1st stage: $\ln(s_{g\|u})$	1st stage: $\ln(s_{u\|IN})$
LNboxoffice	0.384**	0.394**	0.029**	0.355**	0.068**	0.098**
	(0.043)	(0.044)	(0.005)	(0.012)	(0.006)	(0.008)
decay	-0.024**	-0.057**	-0.002**	-0.024**	0.002*	-0.010**
	(0.003)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
$decay^2$		0.001**				
		(0.0002)				
window	-0.003	-0.004	-0.0004	-0.003*	-0.001	0.0003
	(0.002)	(0.002)	(0.0006)	(0.002)	(0.001)	(0.001)
$\ln(s_{j\|g})$	0.290**	0.265**	0.941**			
	(0.070)	(0.073)	(0.005)			
$\ln(s_{g\|u})$	0.214**	0.252**	0.941**			
	(0.080)	(0.078)	(0.007)			
$\ln(s_{u\|IN})$	0.295**	0.283**	0.930**			
	(0.073)	(0.074)	(0.006)			
Action	-0.331**	-0.342**	-0.021+	0.167**	0.049**	-0.663**
	(0.060)	(0.061)	(0.011)	(0.032)	(0.017)	(0.022)
Suspense	-0.367**	-0.366**	-0.040*	0.282**	0.082**	-0.919**
	(0.089)	(0.090)	(0.016)	(0.040)	(0.022)	(0.027)
Comedy	-0.366**	-0.375**	-0.026*	0.122**	0.056**	-0.688**
	(0.060)	(0.061)	(0.011)	(0.031)	(0.017)	(0.021)
Drama	-0.334**	-0.343**	-0.040**	0.073*	0.051**	-0.564**
	(0.066)	(0.068)	(0.012)	(0.032)	(0.017)	(0.022)
Horror	-0.363**	-0.363**	-0.087**	0.598**	0.148**	-1.284**
	(0.079)	(0.081)	(0.020)	(0.049)	(0.027)	(0.033)
To instrument $\ln(s_{j\|g})$:						
Total log box office				-0.079**	0.013**	0.055**
				(0.002)	(0.001)	(0.002)
Total decay				0.009**	-0.001*	-0.008**
				(0.001)	(0.0004)	(0.0004)
To instrument $\ln(s_{g\|u})$:						
Total log box office				-0.002	-0.074**	0.067**
				(0.003)	(0.002)	(0.002)
Total decay				0.004**	0.009**	-0.012**
				(0.001)	(0.001)	(0.001)
To instrument $\ln(s_{u\|IN})$:						
Total log box office				0.004**	0.0004	-0.018**
				(0.001)	(0.001)	(0.001)
Total decay				-0.001*	-0.0001	0.003**
				(0.0004)	(0.0002)	(0.0008)
Constant	-7.968**	-7.925**	-4.646**	-2.163**	-0.610**	-1.439**
	(0.378)	(0.377)	(0.039)	(0.106)	(0.057)	(0.071)
Observations	5385	5385	5385	5385	5385	5385
F-statistic				114.17	105.10	169.34
R-squared	0.68	0.67	0.94	0.60	0.58	0.69

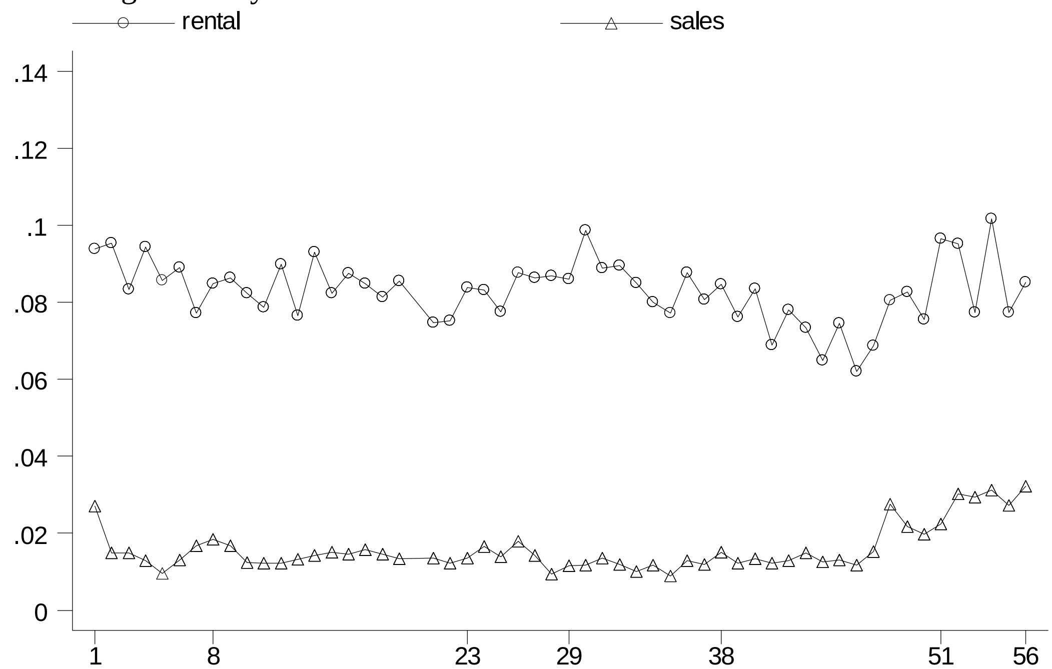
Notes: Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%
The omitted genre is Family.
Video *j* belongs to genre-newness nest *g* and genre nest *u*.

Table 3. Changes in home video revenues from delaying a theatrical release from May 2001 to September 2001

	Sales		Rentals		Change		NET
	pre	post	pre	post	Sales	Rentals	Sales+Rentals
Actual Box office: $263.5 million	90.3	77.9	31.7	34.5	-12.4	2.9	-9.5
	(8.2)	(7.4)	(1.8)	(2.0)			
Box $50m	37.9	32.8	12.9	14.0	-5.1	1.2	-4.0
	(2.6)	(2.5)	(0.7)	(0.7)			
Box $100m	54.5	47.1	18.8	20.5	-7.4	1.7	-5.7
	(4.1)	(3.8)	(1.0)	(1.0)			
Box $150m	67.4	58.2	23.4	25.5	-9.2	2.1	-7.1
	(5.5)	(5.0)	(1.2)	(1.3)			
Box $200m	78.3	67.5	27.3	29.8	-10.7	2.5	-8.2
	(6.7)	(6.1)	(1.5)	(1.6)			
Box $250m	87.8	75.8	30.8	33.6	-12.0	2.8	-9.2
	(7.9)	(7.1)	(1.8)	(1.9)			

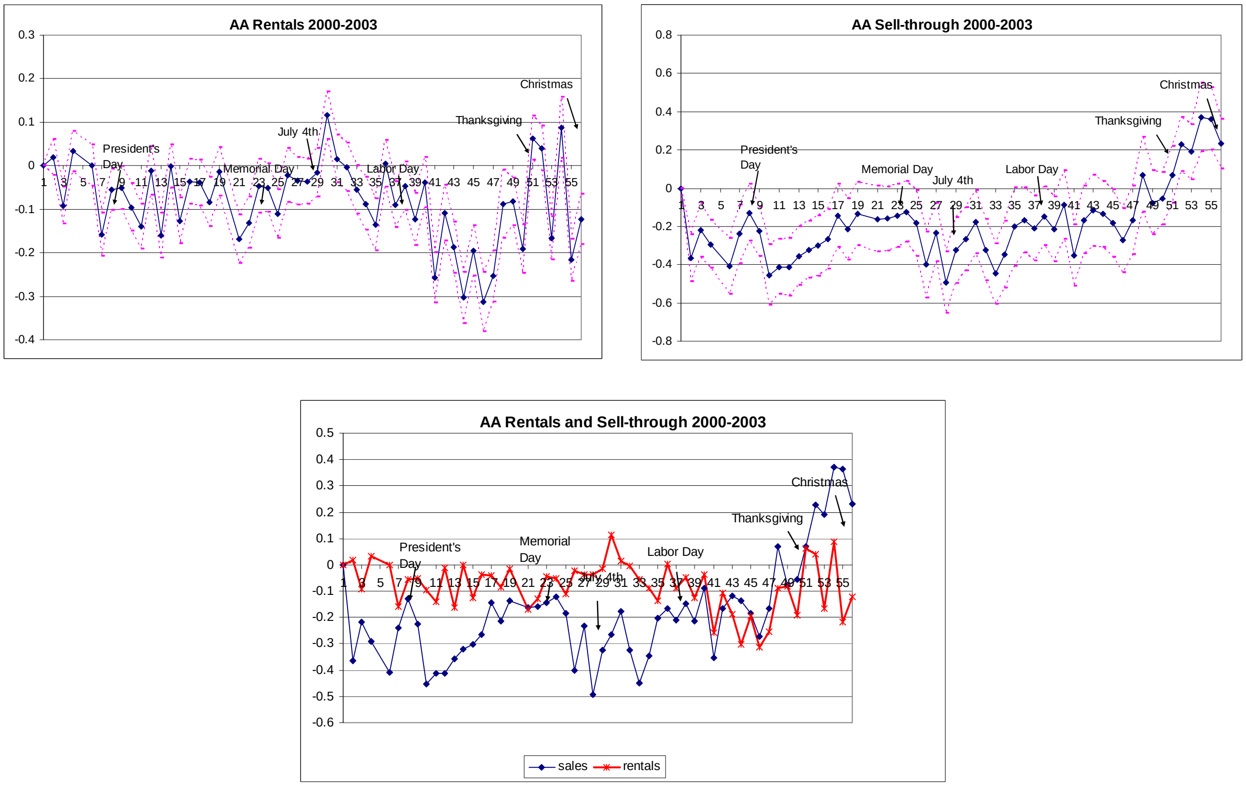
Notes: The columns "pre" indicate revenues for the May theatrical release date.
The columns "post" indicate revenues for a September theatrical release date.
The estimates assume the movie has a window of 23 weeks and is a Family movie.
The predictions for "Shrek" are shown along with counterfactuals that vary the quality of the movie (i.e., box office).
The standard errors were calculated by bootstrapping from the asymptotic distribution of the estimated coefficients 100 times.

Figure 1. Average Industry Share: AA Rentals and Sales 2000-2003



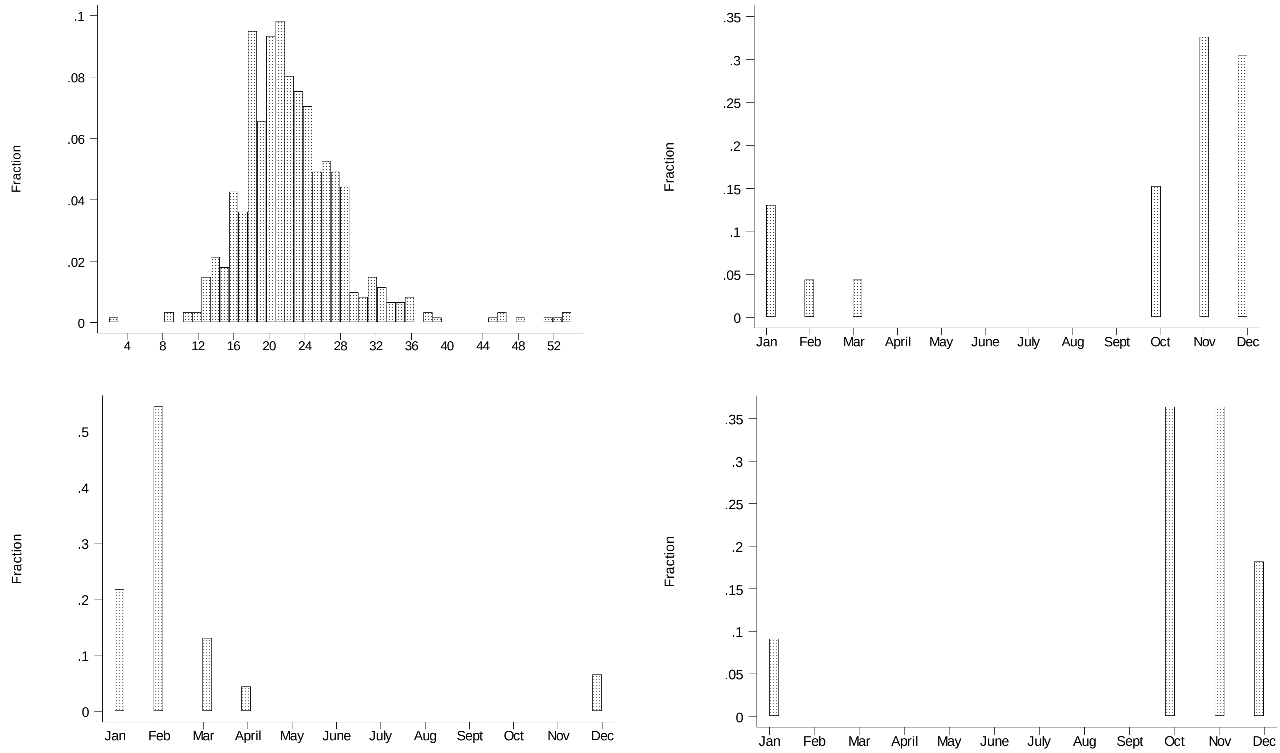
Note: The timing in holidays is standardized across years to yield 56 weekly dummies.

Figure 2.



Top Left Panel: Estimated weekly coefficients for rental market.
Top Right Panel: Estimated weekly coefficients for sales market.
Bottom Panel: Estimated weekly coefficients for both sales and rental markets.
Notes: Deviations of two standard errors are indicated by dashed lines. The timing in holidays is standardized across years to yield 56 weekly dummies.

Figure 3.



Top left panel: Histogram of window lengths (in weeks) for all movies.
Top right panel: Month of video release for movies with July theatrical release
Bottom left panel: Month of video release for movies with September theatrical release
Bottom right panel: Month of video release for movies with July theatrical release and box office less than $25 million