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# 1 Introduction

During the July 4<sup>th</sup> 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 4<sup>th</sup> 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 4<sup>th</sup> 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.

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, 2004)

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



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).<sup>3</sup> Since 1996, revenue sharing has become a fairly common practice for VHS. Instead of a fixed price per unit,

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 677ths. 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.<sup>5</sup> 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 av



### 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:

$$u_{ijt} = \mu_{jt} + \epsilon_{ijt}$$

where  $\mu_{jt}$  is the mean utility and  $\epsilon_{ijt}$  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.<sup>6</sup> I normalize the utility of all consumers from the outside good (good 0) to be zero. The unobservable error term  $\epsilon_{ijt}$  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:

$$\mu_{jt} = \beta_j + \gamma_j W_{jt} + \alpha_j Q_{jt} + \delta_j r_j + \eta_j I_{jt}$$

where  $\beta_j$  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  $j$ ,  $\eta_j$  is the underlying seasonal effect in demand for the inside

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<sup>6</sup> 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  $\alpha$ ,  $\beta$  and  $\gamma$  on the inclusive values for each nest.<sup>7</sup> (See Appendix for formulas.) The parameters  $\alpha$ ,  $\beta$  and  $\gamma$  represent the degree of substitution among alternatives in the genre-newness, genre, and inside nests. For instance, when the coefficient  $\alpha$  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  $\alpha$ ,  $\beta$  and  $\gamma$  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

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 its utility.

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.<sup>8</sup> 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  $\ln(s_{g/\mu})$ , 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.<sup>9</sup>

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.<sup>10</sup> Since the major holidays fall on different

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<sup>8</sup> 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.

<sup>9</sup> By definition, the instruments are equal to zero when there is only one video in a nest.

<sup>10</sup> 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 (

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

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.<sup>13</sup> 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).<sup>14</sup>

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.

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<sup>13</sup> 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.

<sup>14</sup> 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.





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  $t = 2, \dots, 56$ ) 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 k.0232 periods of televi

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.<sup>15</sup>

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.

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<sup>15</sup> 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.

(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

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.

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.<sup>19</sup> 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 4<sup>th</sup> 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 4<sup>th</sup> 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).<sup>20</sup>

A simple regression on the gap between total box office of movies near July 4<sup>th</sup> 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

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<sup>19</sup> 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.

<sup>20</sup> 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 4<sup>th</sup> and Labor Day decreases by one movie. Although fewer movies are being shown near July 4<sup>th</sup> 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 calcula



In the sales market, predicted revenues dr

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 4<sup>th</sup> 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





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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:  $\zeta_{jt}$ ,  $\beta X_{jt}$ ,  $\beta Y_{gt}$ ,  $\beta Z_{ut}$ ,  $\beta W_{IN,t}$ , 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:

$$\frac{e^{\zeta_{jt} + \beta X_{jt} + \beta Y_{gt} + \beta Z_{ut} + \beta W_{IN,t}}}{\sum_{j \in I} e^{\zeta_{jt} + \beta X_{jt} + \beta Y_{gt} + \beta Z_{ut} + \beta W_{IN,t}}}$$

Table 1. Home Video Rentals

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	OLS		1st stage: $\ln(s_{j g})$	1st stage: $\ln(s_{g u})$
LNboxoffice	0.183**	0.175**	0.005**	0.443*	0.046**	0.060**

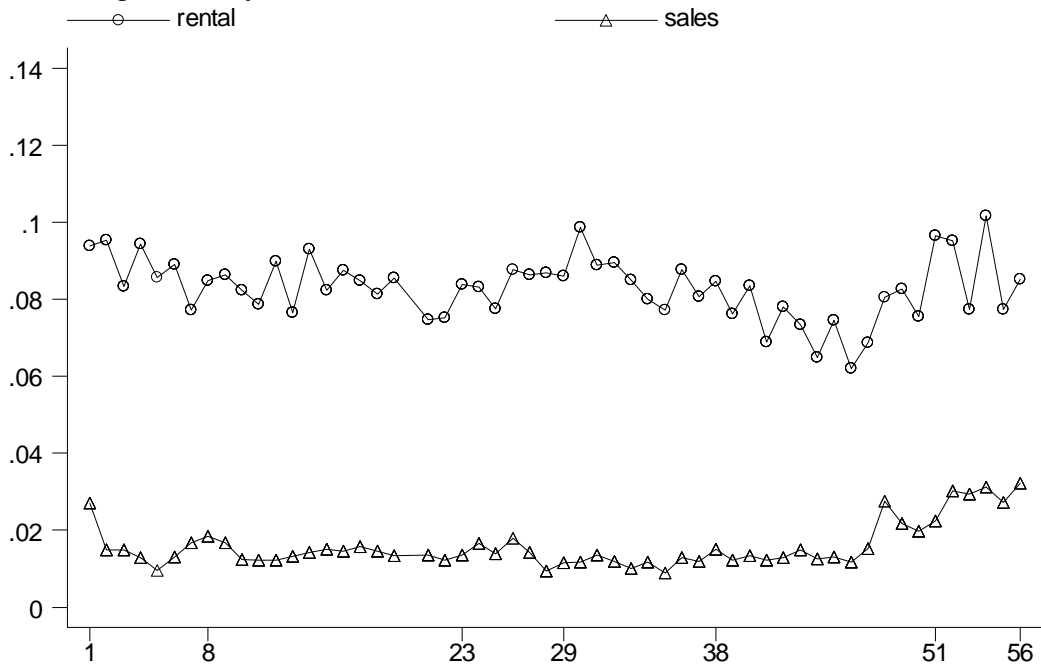
Notes: Robust standard errors in parentheses  
+ significant at 10%; \* significant at 5%; \*\* significant at 1%  
The omitted genre is Family.  
Video  $j$  belongs to genre-newness nest  $g$  and genre nest  $u$ .







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.

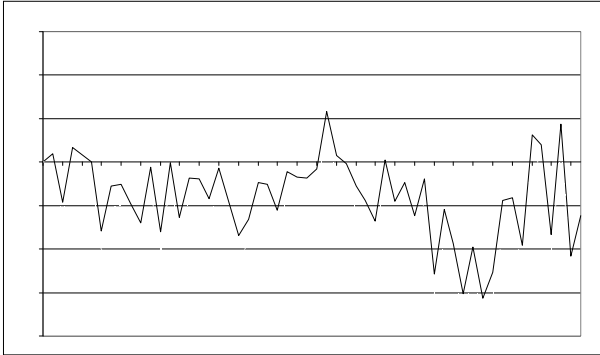


Figure 3.