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The Competitive Dynamics of New DVD Releases

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Abstract. We study the market for new (movie) DVDs in the United States. Our demand model captures seasonality, freshness (i.e., time between theatrical and DVD release), and state dependence. We also develop a structural model of dynamic competition in which studios balance waiting for high-demand weeks, against reduced freshness, and against competitive crowding. We find that studios emphasize DVD revenues from larger movies (by theatrical revenue) over DVD revenues from smaller movies. Studios also emphasize revenue from consumers who prefer larger and fresher movies. These behaviors are consistent with managerial conservatism: studio executives forgo DVD revenues from smaller movies to ensure the DVD success of larger movies.

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Keywords: dynamic competition • time-nonhomogeneous Markov perfect equilibrium • release timing • motion picture industry • managerial conservatism

1. Introduction

For movie studios, choosing the release date of a new DVD is a crucial, yet complex, decision. Consumers have seasonally varying demand for new DVDs (Chiou 2008). Therefore, studios have an incentive to wait to release a movie in a seasonal peak demand week. However, consumers also value freshness of new DVDs—i.e., DVDs released soon after theatrical release (Hennig-Thurau et al. 2007, Mukherjee and Kadiyali 2011). Thus, studios face a tradeoff between waiting for higher-demand weeks and capitalizing on a movie's freshness. Further, competitive considerations complicate studios' decision. In response to seasonal consumer preferences, studios release more DVDs close to seasonal peak-demand weeks, leading to crowding (Chiou 2008, Einav 2010). Thus, in addition to the demand seasonality (and freshness sensitivity), studios also must consider their rivals' DVD release dates.

Moreover, studio executives may exhibit managerial conservatism in their DVD release date choices. Conservatism is when managers choose a traditional form of behavior or industry practice rather than being outliers from the herd with a nontraditional/experimental behavior or strategy. For example, Zwiebel (1995) models a competitive equilibrium where each manager chooses an action taking into account other managers' choice. Managers know their own ability, but principals (owners or investors) do not. Zwiebel shows that incomplete information about manager and project outcomes may lead to principals evaluating managerial ability by relative performance. Managers who choose the "standard action" are evaluated with a more accurate benchmark than managers with nonstandard choices. Therefore, choosing an outlier strategy carries the risk of not having a well-established benchmark for evaluation; the established benchmark is based on traditional strategies. For example, an outlier strategy might generate profits later or with greater uncertainty compared to the industry's traditional strategy that is profitable sooner or more certain. This leads to herd behavior, with most managers targeting well-established benchmarks. There are other agency models that generate similar herding behavior; see Section 2 for more details.

Prior studies of the movie industry have found evidence consistent with conservatism in pretheatrical decision making, including choices in casting (Ravid 1999, Basuroy et al. 2003), pricing in theatrical distribution (Orbach and Einav 2007), and release timing for theatrical distribution (Einav 2010). While these studies investigate pretheatrical decisions, our paper examines posttheatrical decisions. In these posttheatrical decisions, on the one hand, theatrical revenues are known, and hence movie quality is more visible. This might mitigate revenue uncertainty for managers, freeing them from conservative to nontraditional choices. On the other hand, the revelation of information in the theatrical channel might reinforce theatrical channel conservatism. For example, given the historical centrality of blockbusters in Hollywood, studios likely do not want to see theatrical successes failing in DVD release because of poor release decisions. Therefore, studio executives might be conservative and pay more attention to the DVD revenues of larger (by theatrical revenue) movies, especially if they think their rivals will also do the same.

Our paper develops novel structural econometric models of demand and competition for the new (movie) DVD market. To manage computational and data demands, we draw on the literature in aggregative games. A game is *aggregative* if a player's payoff is a function of her own actions and an aggregator function of the actions of all players.[1] By extension, demand is aggregative if the demand for the products or services offered by a player is a function of her own actions and an aggregator function of the actions of all players. Therefore, to model demand, we employ the aggregate latent class multinomial logit (MNL) random utility model (RUM). We extend this aggregative demand model to account for state dependence (where past purchases may affect utility in the current period) and seasonality.

On the supply side, the empirical model is based on a game of incomplete information. We define the set of consumer-segment–specific aggregative statistics from our demand model to be the state vector in the game. In our context, the state vector summarizes the impact of the incumbents and potential entrants on the expected demand from releasing a movie on DVD on any release date. A time-nonhomogeneous Markov transition kernel describes the (seasonal, time-varying) evolution of the state vector. We solve for the rational (perfect Bayesian) equilibrium, which is the time nonhomogeneous Markov perfect equilibrium (MPE) in release-date choices. We develop a novel conditional choice probability estimator: first, we estimate the transition kernel and the policy functions from the data and then maximize the conditional likelihood (conditional choice probability, given studio beliefs) of the observed release dates.

We apply these econometric models to study new (movie) DVD sales in the United States between 2000 and 2005. We find two distinct consumer segments that vary both in the seasonality of their preferences and their responsiveness to DVD attributes including prior theatrical success and freshness. To uncover possible conservatism, we estimate a series of competition models with nested flexible maximands that sequentially consider segment, studio, time, and movie asymmetries in studios' objective functions. The data suggest that managers pay more attention to maximizing the DVD revenues of larger (by prior theatrical success) movies and emphasize DVD demand from consumers who prefer larger movies. Therefore, the evidence is consistent with conservatism: studio executives forgo revenues from movies that were less successful in movie theaters, to safeguard the DVD success of movies proven theatrical successes.

Our paper makes the following contributions. Methodologically, the model structure can have several applications. Particularly, most prior studies of seasonality have abstracted from seasonality in competition and only focused on demand seasonality. Further, extant game-theoretic frameworks of competition require restrictive symmetry assumptions (e.g., symmetric payoffs, symmetric rivals, time-symmetric decision rules) that preclude seasonal competition. A strength of our modeling approach is its ability to accommodate flexible (asymmetric) payoff structures, asymmetric rivals, and time-varying (seasonal) marketing mixes, as is common in many seasonality-related applications. Substantively, we add to the empirical knowledge base on an important phenomenon—managerial conservatism—that has received theoretical attention but relatively limited empirical attention. Particularly, empirical studies have found evidence of conservatism based on reduced-form models or based on postestimation patterns of structural estimates. In contrast, by embedding conservatism-consistent payoffs in a structural model, we can obtain drivers of conservatism. Simulations based on structural estimates allow us to examine the effects of conservatism on both market outcomes (release dates) and expected revenues.

2. Literature Review

Our paper relates to the following five broad streams of the literature.

First, our paper relates to models of the revenue of a movie, given movie attributes (such as the genre of the movie) and the revenues of the movie in prior markets or periods. For example, Neelamegham and Chintagunta (1999) and Elberse and Eliashberg (2003) study the diffusion of international box office receipts after domestic release. Luan and Sudhir (2007) study the impact of sequential release strategies on forward-looking consumers in the primary (theatrical) channel. In building our demand model, we use several explanatory variables validated in this literature.

Second, our paper relates to papers that study seasonality in movie demand. For example, Radas and Shugan (1998) use an innovative transformation of time to build a model of seasonal demand. Einav (2007) introduces the idea of capturing seasonal changes in preferences by adding a time-varying fixed effect to the utility of a representative consumer. Chiou (2008) and Mukherjee and Kadiyali (2011) measure whether seasonal market expansions and contractions occur due to intertemporal changes in preferences for movies, or due to concurrent movie releases. Unlike these papers, our demand allows for heterogeneity in seasonal (and other) preferences. Specifically, we embed a Fourier basis in the consumer utility function, which enables a flexible and yet parsimonious capture of seasonality.

Third, our paper relates to a stream of the literature that has studied the optimal release timing of movies (e.g., Krider and Weinberg 1998, Lehmann and Weinberg 2000, Prasad et al. 2004, Ma et al. 2013). The paper most similar in structure and intent to ours is Einav (2010), who studies theatrical release competition. Similar to Einav (2010), we use the solution concept of a perfect Bayesian equilibrium in a game of incomplete information to model release decisions. We extend the demand model in Einav (2007) to account for heterogeneity. We also extend the competition model of Einav (2010) to allow for time-varying strategies and asymmetric firm payoffs. He examines four major holiday weeks and the adjacent weeks. The release-time competition is among the set of movies already present in these weeks competing for release in the peak week rather than adjacent weeks. Our competition model is for all movies that are unreleased in DVD and for all future weeks. Therefore, our model is significantly more general (and complex) and allows for richer and more realistic forms of competition.

Fourth, our study relates to the literature on models of the strategic choices of competing forward-looking firms. Dorazelski and Pakes (2007) provide an excellent description of the MPE framework that is the workhorse for analyses of the strategic decisions of competing forward-looking firms. Recent applications of the framework include Gardete (2016), Hollenbeck (2017), and Shen (2014). Our model of competition methodologically extends these models as follows. First, we modify the baseline model to capture the time nonhomogeneity of the decision environment. Second, by using aggregative statistics derived from the demand model, we can capture the complex competitive dynamics of the release timing game. Third, tractability is a key concern in the dynamic games literature. We develop an estimation strategy that allows for more-flexible firm objective functions, including specifications that vary by both firm and product attribute.

Last, our study is related to the literature on managerial conservatism. As discussed in the introduction, Zwiebel (1995) proposes a principal–agent model where owners do not observe managerial ability. In his model, it is optimal for principals to judge performance by relative ability. Faced with this compensation scheme, managers choose traditional actions rather than nontraditional actions. This is done to ensure that the relative performance is measurable because of well-established outcomes associated with these traditional actions. While Zwiebel's model of conservatism has been invoked in the movie literature to describe managerial behavior (see the paragraph below), it is important to note that other agency models also predict similar behavior. For example, Scharfstein and Stein (1990) propose a model of herding with different information assumptions—in their model, both owners and managers do not know managerial ability, whereas in Zwiebel's model, only principals do not know managerial ability. This results in a preference to fail together rather than fail alone, and hence in herding strategies rather than separating strategies. Another important class of models that also result in herding is signal-jamming models. For example, in Holmström's (1999) (see also Fudenberg and Tirole 1986) model, managers do not know their own ability. Driven by career concerns, managers prefer strategies/investments where failure can be attributed to external circumstances rather than poor managerial ability. This also leads to herding in safe or traditional strategies.

As mentioned in the introduction, previous movie studies have found evidence consistent with conservatism in pretheatrical decision making. For example, using reduced-form models, Ravid (1999) and Basuroy et al. (2003) find that studios disproportionately use actors with past record of success or "star power" to improve movie revenues when movie quality (measured by critics' ratings) is low even though star power has no revenue impact for high-quality movies. As Ravid (1999, p. 489) states, "The industry faces extreme uncertainty and executives might simply be wished to the 'covered' in case a project fails." Orbach and Einav (2007) study reasons for uniform pricing of movies in theaters. They rule out fairness concerns, quality uncertainty and unstable demand, and agency reasons (among others) for this pricing. They conclude that this pricing scheme is conservative and follows longstanding tradition. Similarly, Einav (2010) finds evidence of conservatism: studio executives herd in their release decisions, to avoid the risk of being a lone (unsuccessful) theatrical release in a nonpeak week. While his model of both demand and supply is structural, his evidence for conservatism is that studios release more movies in peak periods than is justified by demand in peak weeks. Note that Einav finds evidence for conservatism after structurally estimating demand and supply, rather than by embedding within structural estimation. We extend the standard model of dynamic competitive behavior to measure if DVD release decisions reflect a differential emphasis on the revenue from different movies and consumers. As discussed in Section 6, we test for a variety of specifications (inside the structural supply estimation) to measure the presence and form of conservatism. Finally, we contribute to the related empirical knowledge base by measuring the consequences of conservatism for revenues and release dates.

3. Data

Nielsen VideoScan collects purchase data from retailers at the point of sale. We obtain weekly release dates, units sold, and prices for all DVDs released in the United States between 2000 and 2005, adjusted for the universe of coverage. We use this period before the rise of alternative posttheatrical distribution. We use the Consumer Price Index in the United States to deflate prices to be in December 2005 dollars. Between 2000 and 2005, our period of study, there were six major DVD studios/distributors: Columbia, Disney, Fox, Paramount, Universal, and Warner. We further exclude from our sample three kinds of movies that are unlikely to compete with larger movies: direct-to-DVD movies, movies with limited theatrical success (movies that grossed less than 10 million U.S. dollars in theatrical revenue), and older movies being rereleased on DVD. These types of movies constitute a different market outside of our new-movie release-timing game.

Each DVD has a short product lifecycle (Rennhoff and Wilbur 2011), and each movie exerts greater competitive pressure on other movies early in its lifecycle. Hence, we focus on the first 13 weeks after DVD release. We do not observe DVD releases prior to January 2000 (the release date is required to compute the freshness of the movie). Therefore, we drop the first 12 weeks of market-share data when estimating the demand model. We estimate our model on market-share data of 808 DVDs sold over 300 weeks. In the release-timing model, we drop movies that entered the game in the first 13 weeks of 2000 (to compute variables needed for estimating the game) and estimate on data from 730 movies across 299 weeks. Additionally, we collect data on movie-specific descriptors (for example, theatrical revenue). Finally, we use the monthly sales of DVD players in the United States from 2000 to 2005, collected by the Consumer Electronics Association, to construct the market size in each period. Table 1 presents the descriptive statistics of the final sample.

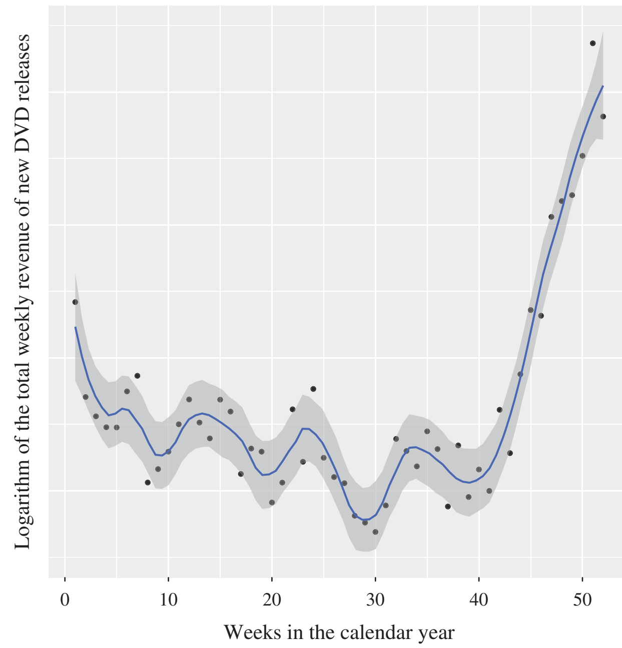
Figure 1 illustrates seasonality in weekly DVD demand. In Figure 1, we plot the logarithm of the average total weekly DVD revenue (averaged over the six years of data in our data set). We include a LOESS (nonparametric) regression to depict the cyclicality in sales over the year. Figure 1 shows that DVD demand is strongly seasonal with large predictable variations over the course of a year. Figure 2 describes the observed density of DVD releases for each studio over the course of the calendar year. Figure 2 shows that while Universal focuses on the holiday season, smaller studios (grouped under "Other studios") stay away from releasing DVDs in this period. Further, Disney's

Table 1. Descriptive Statistics

Studio	Number of DVDs released	Theatrical to DVD release[a]	Price[b]	Theatrical revenue[c]
Columbia	159	20.41 (5.27)	18.41 (1.74)	55.58 (55.18)
Disney	141	24.43 (6.48)	18.68 (1.91)	68.89 (62.25)
Fox	92	23.44 (5.86)	18.76 (2.85)	64.83 (70.97)
Paramount	77	23.28 (4.18)	19.94 (2.68)	58.08 (40.60)
Universal	145	23.49 (6.16)	18.49 (1.74)	72.90 (66.63)
Warner	168	22.63 (5.49)	18.22 (1.61)	62.75 (70.20)
Other studios	26	19.96 (2.68)	17.87 (1.66)	23.34 (15.01)
Industry	808	22.74 (5.80)	18.60 (2.06)	62.80 (62.65)

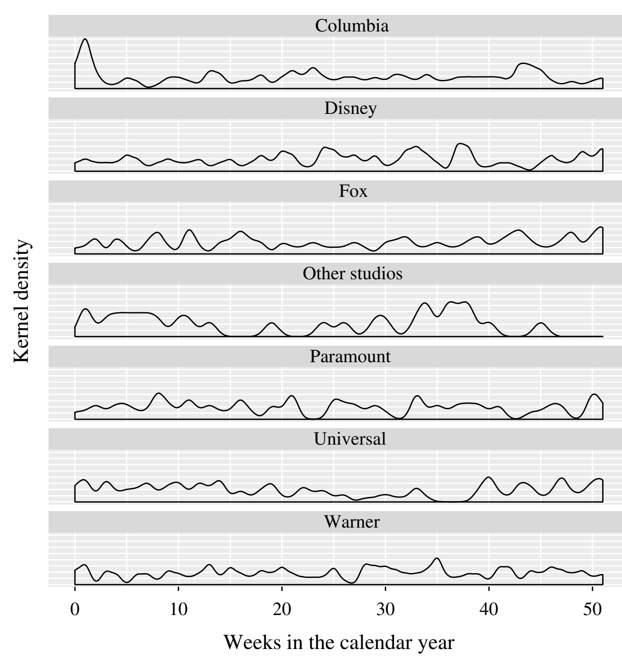
Note. Average values, with standard deviations in parentheses.
[a]Number of weeks between theatrical and DVD release.
[b]In U.S. dollars.
[c]In millions of U.S. dollars.

Figure 1. (Color online) Seasonality in New DVD Revenue



Notes. Average of the logarithm of the total weekly revenue of new DVD releases. LOESS regression and associated standard errors.

Figure 2. Seasonality in New DVD Release Dates



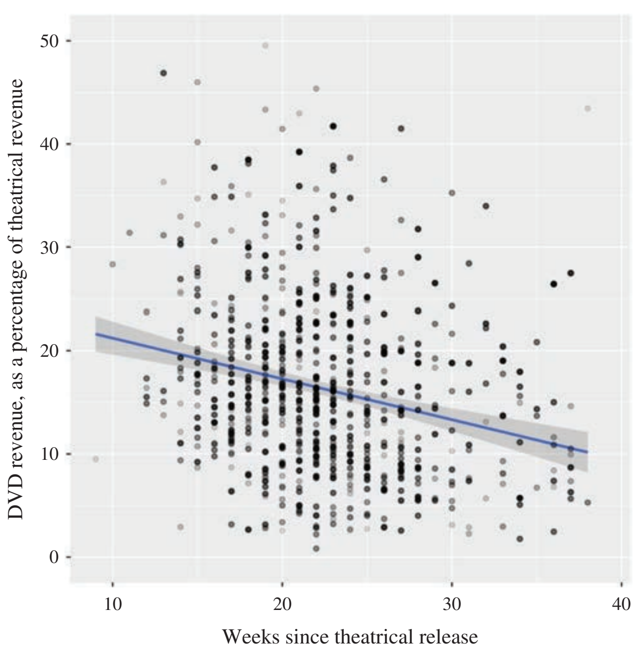
Note. Density of new DVD releases, by studio, averaged across 2000–2005.

releases focus on the earlier weeks of the holiday season while Columbia focuses on the last weeks of the holiday season. The difference in release date choices is likely driven by both differences in demand seasonality for the studios' products (e.g., animation movie DVDs might have different seasonality than action movie DVDs) and differences in studios' focus on demand from different consumer segments. This points to the need for studio-specific (i.e., asymmetric) payoff functions.

Figure 3 plots the ratio of total DVD revenue to total theatrical revenue, with time since theatrical release. Note that Figure 3 does not account for seasonality. As DVD releases are delayed to target higher-demand weeks, the estimate of the impact of freshness of profits is positively biased in Figure 3. Therefore, this is a conservative test of the negative impact of freshness on DVD revenue. However, Figure 3 shows a strong negative relationship between freshness and DVD revenue, indicating that freshness is likely a major force in the release decision calculus of studios.

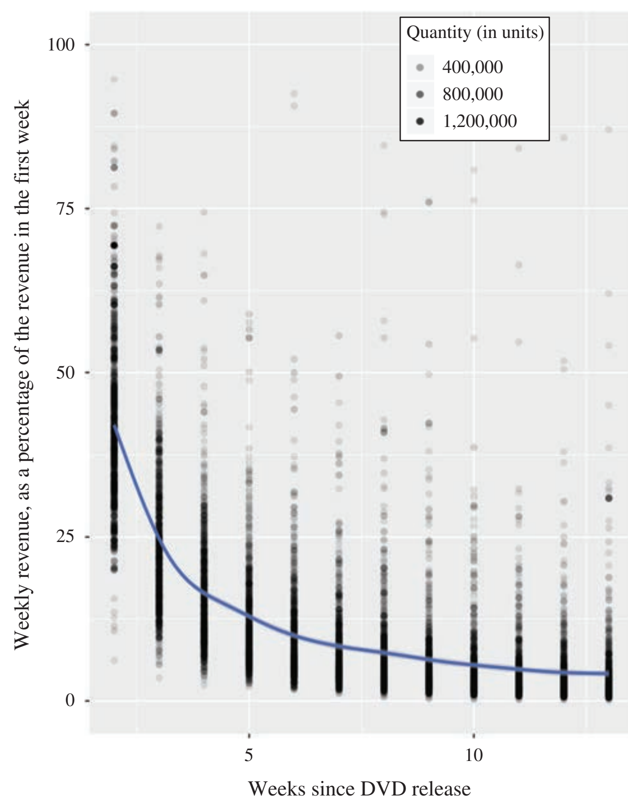
Figure 4 plots the weekly revenue of each DVD, each week after release, expressed as a percentage of the revenue in the release week. We include a generalized additive model (nonparametric) regression to capture the average change in revenue after release. Figure 4 provides strong evidence that DVD revenues decrease steeply after release: on average, revenue in week 13 is 4% of the revenue in week 1. Figure 5 plots the weekly prices of each DVD, expressed as a percentage of the average price of the DVD. Figure 5 shows that there is no similar decrease in prices post DVD release. Thus, consumers lack an incentive to strategically wait to purchase a DVD in future periods (leading to the sharp decrease in sales after release, as seen in Figure 4). Hence, we do not model consumers as being forward looking.

Figure 3. (Color online) Decrease in Revenue After Theatrical Release



Notes. DVD revenue, divided by the theatrical revenue of the movie. The color of the bubble corresponds to the theatrical revenue of the movie. Regression and associated standard errors.

Figure 4. (Color online) Decrease in Revenue After DVD Release



Notes. Weekly quantity sold of a DVD after release, expressed as a percentage of the quantity sold of the DVD in the first week after release. The color of the bubble corresponds to the number of DVDs sold. Nonparametric regression and associated standard errors.

4. Demand for DVDs

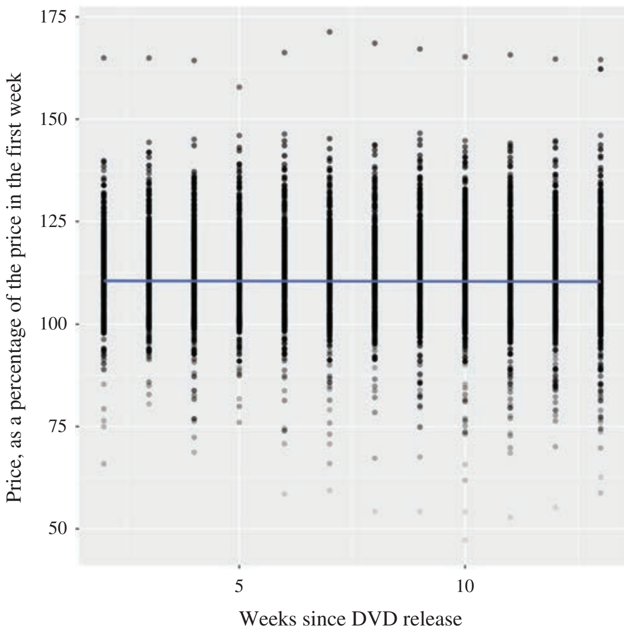
4.1. Model Specification

We build on the aggregate latent class multinomial logit model (see Besanko et al. 2003 and Hess et al. 2011 for a discussion of robustness). In more recent applications, Berry and Jia (2010), Soysal and Krishnamurthi (2012), and Pattabhiramaiah et al. (2018) use similar models to study consumer preferences in the airlines, fashion, and print newspaper industry, respectively.

We model the indirect utility (u_{dsw}) of a consumer in segment s purchasing a DVD d in week w as[2]

$$u_{dsw}(D_{sw}) = T_{dsw} + \beta_{Ds} D_{sw} + \beta_{ps} \log(p_{dw}) + \beta_{TRs} \log(TR_d) + \beta_{IMDbs} IMDb_d + \beta_{xs} x_d + \xi_{dw} + \varepsilon_{dsw}, \quad (1)$$

Figure 5. (Color online) Price After DVD Release



Notes. Weekly price of a DVD, expressed as a percentage of the price of the DVD in the first week after release. The color of the bubble corresponds to the price of the DVD. Regression and associated standard errors.

where D_{sw} is a dummy indicating if the consumer purchased a DVD in the last period, T_{dsw} is the time-varying component of utility, p_{dw} is the price, TR_d is the theatrical revenue, $IMDB_d$ the rating of the movie on the Internet Movie Database (IMDb),[3] and x_d is a vector of dummies indicating the genre, if the DVD is rated R, if the DVD is animated, and the studio that produced the movie. β_{Ds} is a state dependence parameter that indicates if a consumer obtains utility/disutility from purchasing a DVD in a period if they also purchased a DVD in the preceding period, β_{ps} is the price sensitivity parameter, β_{TRs} is the responsiveness of the segment to past theatrical success, β_{IMDbs} is the responsiveness of the segment to the rating on IMDb, and β_{xs} is a vector of genre, R rating, animated status, and studio fixed effects. ξ_{dw} accounts for unobserved week-specific DVD quality, while ε_{dsw} (independent and identically distributed (i.i.d.) Gumbel) accounts for any remaining DVD-, segment- and week-specific idiosyncratic variations in the evaluation of a DVD. To set scale, we model the indirect utility ($u_{0sw} = \varepsilon_{0sw}$) of a consumer in segment s choosing the outside option in week w as i.i.d. Gumbel.

We model the time-varying component of utility (T_{dsw}) as consisting of an intercept, year-specific fixed effects, a periodic (seasonal) change in the preference for buying DVDs, and a weekly decline in utility as the DVD loses its freshness, after release. Following Livera et al. (2011), we approximate the seasonal component (the periodic change) by its Fourier series. The Fourier series is a useful approximation for functions as, under mild regularity conditions, the Fourier series converges to a true (periodic) function. Parseval's theorem implies that the Fourier series polynomial is the unique best trigonometric polynomial approximation to a true (periodic) function. Extant papers use week-specific fixed effects to control for seasonality in preferences (see Einav 2007 for a discussion). Extending the fixed-effects–based model to track heterogeneous seasonal preferences places large demands on the data, with week-specific instruments required for week- and segment-specific fixed effects. Consequently, prior studies modeled consumers as being homogeneous in the seasonality of their preference for buying a DVD (cf. Chiou 2008, Mukherjee and Kadiyali 2011). The orthonormal basis of sine and cosine waves is a general, robust, and parsimonious way to capture seasonal variation in preferences. To account for the last component—freshness—we include the length of time between theatrical and DVD release and the length of time since DVD release. Specifically, we model T_{dsw} as

$$T_{dsw} = \beta_{1s} + \beta_y + \sum_{h=1}^{H}\left(a_{hs}\sin\left(\frac{2\pi hr}{52}\right) + b_{hs}\cos\left(\frac{2\pi hr}{52}\right)\right) + \beta_{WBs}\log(WB_d) + \beta_{WRs}\log(WR_{dw}), \tag{2}$$

where β_{1s} is a segment-specific intercept, β_y is a year-specific fixed effect, a_{hs} and b_{hs} are the Fourier coefficients, WB_d is the number of weeks between theatrical and DVD release, and WR_{dw} is the number of weeks since DVD release, while β_{WBs} and β_{WRs} are coefficients on the last two terms, respectively. H is the number of harmonics of the fundamental frequency (corresponding to annual periodicity) included in the model, r is w modulo 52, the specific week of the year, and y is the year to which w corresponds. Increasing H improves the approximation at the cost of increasing the number of estimated parameters. Our formulation allows for segment-specific heterogeneity on *all* attributes (average propensity to purchase a DVD, state dependence, price, theatrical revenue, freshness, and seasonality).

Note that state dependence is category-level and not product-level. In a model with product-specific state dependence, computing the market-share function requires knowledge of a consumer's complete purchase history. As the state space must span all possible combinations of prior purchases, the cardinality of the state space has exponential order in the number of available alternatives. This is computationally intractable in our context due to the large number of DVD releases. To reduce the computational burden, some prior studies have treated purchase decisions over different products as being independent (Luan and Sudhir 2007). However, these models do not account for what other products (excluding the focal product) were purchased in prior periods. This assumption is particularly restrictive in our study since the weekly changing set of competing alternatives is an important driver of DVD revenues and hence release-date choices.

Following Berry et al. (1995), we treat measured market shares as being analogous to population probabilities. As is common for aggregate logit models, we assume that each consumer chooses one good (inclusive of an outside option), in each week.[4] Let F_{sw} represent the proportion of the consumers in a segment that purchased a DVD in the week prior to w—i.e., in week, $w-1$. F_{sw} is unobserved in our demand model. We infer F_{sw} from the cumulative probability of consumers in a segment purchasing any DVD in the prior period:

$$F_{s(w+1)} = F_{sw} \sum_{d\in\mathbb{C}_w} \frac{\exp(u_{dsw}(D_{sw}=1))}{1+\sum_{i\in\mathbb{C}_w}\exp(u_{isw}(D_{sw}=1))} + (1-F_{sw}) \sum_{d\in\mathbb{C}_w} \frac{\exp(u_{dsw}(D_{sw}=0))}{1+\sum_{i\in\mathbb{C}_w}\exp(u_{isw}(D_{sw}=0))}, \quad (3)$$

where $\mathbb{C}_w$ denotes the set of DVDs available for purchase in week w, $u_{dsw}(D_{sw}=1)$ is the utility from purchasing DVD d to a consumer in segment s who purchased a DVD in the preceding period (i.e., $w-1$), and $u_{dsw}(D_{sw}=0)$ is the utility from purchasing DVD d to a consumer in segment s who did not purchase a DVD in the preceding period (i.e., $w-1$). The segment-specific market share of DVD d in segment s, in week w, $mktsh_{dsw}$, where u_{dsw} is the utility to a consumer in segment s and $\mathbb{C}_w$is the choice set of DVDs available for purchase, is

$$mktsh_{dsw} = F_{sw} \frac{\exp(u_{dsw}(D_{sw}=1))}{1+\sum_{i\in\mathbb{C}_w}\exp(u_{isw}(D_{sw}=1))} + (1-F_{sw}) \frac{\exp(u_{dsw}(D_{sw}=0))}{1+\sum_{i\in\mathbb{C}_w}\exp(u_{isw}(D_{sw}=0))}. \quad (4)$$

The total market share is the weighted sum of the segment-specific market shares, weighted by the class allocation probabilities:

$$mktsh_{dw} = \sum_{s\in S} P_s mktsh_{dsw}, \quad (5)$$

where P_s is the fraction of consumers who are a member of segment s, and S is the set of all segments. The measured share is constructed from the quantity of DVD $d$purchased in week w and the total market size (the number of households that own DVD players in the United States in week w).

State dependence is identified through both changes in the set of DVDs released and the seasonality of consumer preferences over the course of the year. In a week, the set of DVDs available and seasonality drive the probability of purchase, and hence the fraction of purchasing consumers in each segment. The variation in the available set of DVDs and the seasonality in preferences induces a variation in the fraction of consumers who purchase DVDs across weeks. This allows for the identification of category-level state dependence. A parallel argument can be found in Einav (2007) where the identification of market expansion rests on seasonality in preferences in the theatrical channel and choice sets, and in Horsky et al. (2012) where the identification of state dependence rests on longitudinal changes in the marketing mix, and hence purchase likelihoods, of different brands.

We draw on the arguments of Einav (2007) and Chiou (2008) in formulating our instrumentation strategy. There is a long lead time between when studios make release decisions and a release date, with many intervening DVD releases. Hence, it is unlikely that movie-specific differences in freshness sensitivity significantly impact release timing. If the release decisions of studios do not materially depend on such idiosyncratic differences in freshness sensitivity, then as the structural errors are by construction orthogonal to preference seasonality and attributes, the structural errors are orthogonal to aggregate market characteristics (for example, the number of recently released DVDs), which can hence be used as instruments in the demand model. Controlling for seasonality, what drives variation in aggregate market characteristics? The movie production process is long and unpredictable. The variation in the nature and number of movies produced causes exogenous interyear variation in the market characteristics. Thus, the structure of the entertainment market allows us to construct the following instruments: for each studio, in each week, the count, and the mean and the variance (first two moments) of the prior theatrical revenue, number of weeks between theatrical and DVD release, numbers of weeks since DVD release, and price, of DVDs available for purchase.

4.2. Demand Model Estimates

We use the generalized method of moments to estimate the model (the estimation algorithm is described in Appendix A). For parsimony, we test for model components sequentially. In the two-segment model, we find that the data support using the first seven harmonics of the fundamental frequency (we model seasonality as having annual periodicity) to model seasonality in consumer preferences, as the coefficients on the eighth harmonic are not jointly significant. Next, we increase the number of consumer segments in the model. We find the class allocation probabilities are not jointly significant in the three-segment model. Therefore, the three-segment model is not supported in the data. We find that the data support the inclusion of homogeneous studio fixed effects in the utility function. However, the heterogeneity coefficients on the studio fixed effects are jointly not significant.

A consumer segment comprising of 54% of the consumers is comparatively freshness sensitive in its DVD demand while the other segment is comparatively freshness insensitive. These segments differ (statistically significantly) on the mean propensity to buy a movie on DVD, responsiveness to price, theatrical success, freshness, consumer rating, and measures of content such as the MPAA rating of the movie, its genre, and if the movie is animated or live-action. Table 2 reports the coefficient estimates for all segments.

Table 2. Demand Model Estimates ($N = 9{,}892$)

	Freshness-sensitive segment		Freshness-insensitive segment	
	Coeff.	S.E.	Coeff.	S.E.
Constant	−72.87***	(1.37)	−16.49	(12.10)
Price sensitivity	−4.21***	(0.42)	−3.30***	(0.52)
Theatrical revenue	1.46***	(0.02)	0.79***	(0.03)
IMDb rating	0.09***	(0.02)	0.14***	(0.04)
Theatrical to DVD release	−0.97***	(0.16)	−0.45**	(0.22)
Weeks since DVD release	−1.56***	(0.02)	−1.28***	(0.04)
Rated *R*	1.43***	(0.05)	−0.08	(0.07)
Animated	3.65***	(0.20)	0.83***	(0.29)
Seasonality				
Sine ($h = 1$)	34.71***	(0.26)	−29.38*	(17.80)
Cosine ($h = 1$)	18.74***	(0.23)	−23.48	(15.30)
Sine ($h = 2$)	42.67***	(0.24)	−33.96	(20.80)
Cosine ($h = 2$)	−13.92***	(0.24)	7.04*	(3.75)
Sine ($h = 3$)	9.54***	(0.29)	−12.07	(9.31)
Cosine ($h = 3$)	−13.98***	(0.18)	25.84*	(14.80)
Sine ($h = 4$)	37.44***	(0.25)	9.21*	(4.82)
Cosine ($h = 4$)	−2.83***	(0.24)	19.74	(12.40)
Sine ($h = 5$)	−3.16***	(0.24)	15.42*	(8.34)
Cosine ($h = 5$)	38.78***	(0.24)	2.11	(3.87)
Sine ($h = 6$)	13.59***	(0.21)	6.01	(4.51)
Cosine ($h = 6$)	−14.75***	(0.26)	−6.48**	(3.09)
Sine ($h = 7$)	−2.52***	(0.22)	−2.01*	(1.20)
Cosine ($h = 7$)	15.04***	(0.25)	−5.16**	(2.50)
Genre				
Action/adventure	2.76***	(0.29)	−1.11***	(0.42)
Comedy	3.62***	(0.29)	−1.66***	(0.43)
Drama	3.04***	(0.28)	−1.54***	(0.42)
Family	0.87***	(0.32)	−0.98**	(0.47)
Horror	2.67***	(0.34)	−1.72***	(0.50)
Mystery/suspense	2.82***	(0.31)	−1.49***	(0.44)
Studio				
Columbia	−0.13*	(0.08)	−0.13*	(0.08)
Disney	−0.05	(0.10)	−0.05	(0.10)
Paramount	−0.05	(0.11)	−0.05	(0.11)
Fox	0.03	(0.09)	0.03	(0.09)
Universal	−0.17	(0.08)**	−0.17**	(0.08)
Warner	−0.10	(0.08)	−0.10	(0.08)
Year				
2001	−0.44	(0.47)	−0.44	(0.47)
2002	−0.81*	(0.47)	−0.81*	(0.47)
2003	−1.16**	(0.48)	−1.16**	(0.48)
2004	−1.60***	(0.46)	−1.60***	(0.46)
2005	−2.01***	(0.47)	−2.01***	(0.47)
State dependence	−6.66***	(0.01)	5.11***	(0.01)
Segment size	0.54***	(0.19)	0.46***	(0.19)

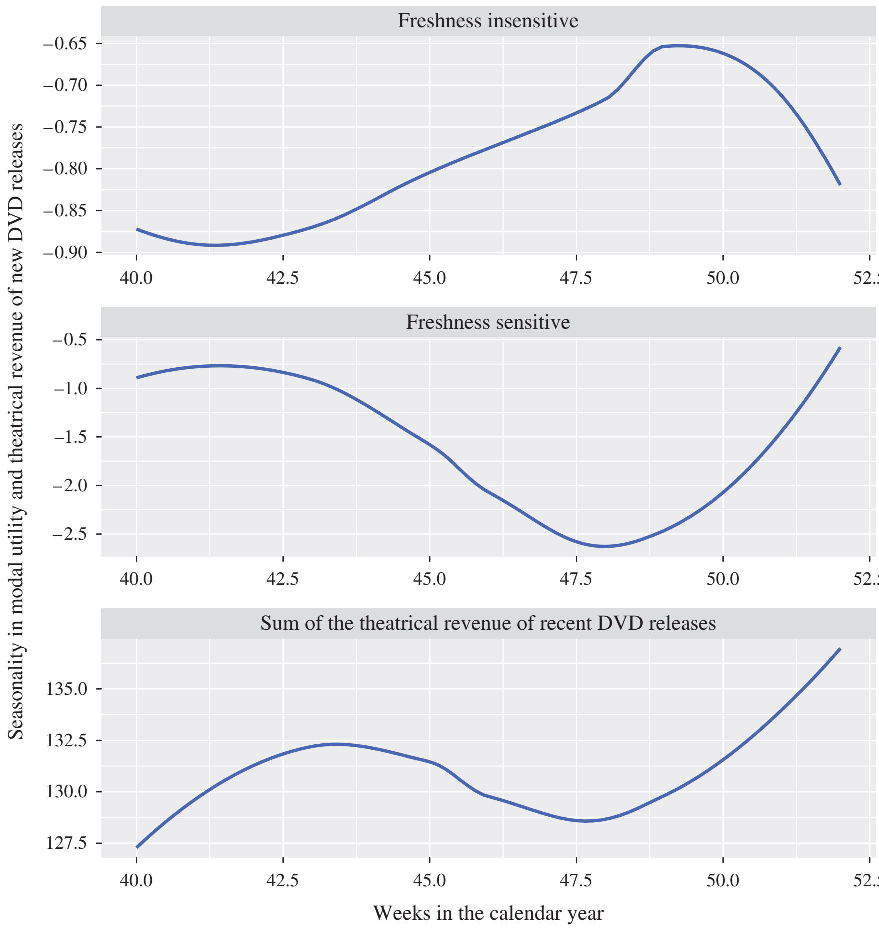
Note. Coeff., coefficient; S.E., standard error; all tests two sided. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We find that the larger segment is more responsive to prior theatrical success than the smaller segment. Further, the larger segment has a stronger preference for action/adventure, animated, family, and mystery/suspense movies, and for movies rated *R*, while the smaller segment is more sensitive to the IMDb rating of the movie. A possible segment membership structure might be as follows: the larger segment might include households with children, while the smaller segment might include households without children. The larger segment might be more driven by the immediate consumption of (mainstream) entertainment, while the smaller segment might be more interested in collecting select DVDs. The larger segment shows negative state dependence; this is consistent with preferring to purchase DVDs irregularly. The smaller segment shows positive state dependence; this is consistent with consumers who have collections, and hence with habit formation.

Figure 6 plots the expected utility of each segment in the fourth quarter of a calendar year (the holiday season). The freshness-sensitive consumers obtain higher utility from purchasing when a large assortment of blockbusters (movies that were highly successful in theaters) are available in the choice set. However, studios wait to release summer blockbusters close to the holiday quarter. The relative staleness of these delayed releases reduces demand from the freshness-sensitive consumers. Expectedly, freshness-insensitive consumers benefit from the improved set of new releases.

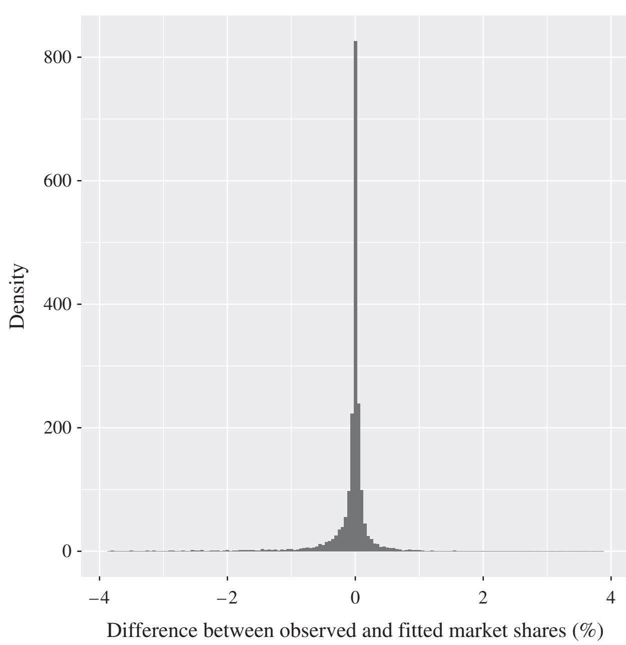
We find strong statistical support for the model and the instrumentation strategy. The J-test admits the null of instrument validity (we cannot reject the null hypothesis that the model is valid; $p > 0.1$). The partial F-statistic of excluded instrument strength exceeds the accepted cutoff of 20. Additionally, we test instruments derived of theatrical revenue and price (the two variables most related to seasonality). We drop instruments derived of these variables, both sequentially and then simultaneously. The difference in J-statistics between the models estimated using the unrestricted and restricted set of instruments is a strict test of the exogeneity of the set of restricted instruments. In all cases, the difference in J-statistics does not reject the null of the exogeneity of the restricted subset of instruments ($p > 0.1$). Further, in all cases, our substantive conclusions remain unchanged. Finally, we also analyze the fit of the demand model. Figure 7 plots a histogram of the difference between the observed and fitted market shares. Figure 7 shows that the fitted shares

Figure 6. (Color online) Seasonality in Utility to the Consumer



Note. Expected utility of buying a new DVD, normed by the absolute median utility.

Figure 7. Fit of Demand Model



Note. Histogram of the difference between the observed and the fitted market shares.

providing a reasonable approximation of the observed market shares, with symmetric and unbiased errors.

5. DVD Release Timing Model

5.1. Model Notation

The following notation (in order of appearance in the exposition) is used in the model. Given DVD d, studio f, segment s, and week w,

- $\varphi = \{\varphi_{fsdw}\}$ is a vector of coefficients that captures the objective function of studios;
- q_{dsw} describes the quantity of DVD d purchased by segment s in week w;
- $0 \leq r < 1$ is a discount factor;
- x_d are the attributes of DVD d;
- $p_d = \{p_{dw}\}$is the vector of prices of DVD d;
- δ_w is the state vector in week w;
- $\upsilon_d = \{\upsilon_{dw}\}$ is the vector of private information shocks across the planning horizon, with density denoted by $d\upsilon$;
- $\mu_{pd}(x_d, \delta_w)$ is the conditional distribution of prices (conditional on DVD attributes and the state vector) with density given by $d\mu_{pd}(x_d, \delta_w)$;

- $a_{d(w,w+1,\ldots)}$ is the vector of actions of DVD d across the planning horizon;
- $\Psi_{d(w+j)}(\delta_{w+j} \mid \delta_w, a_{d(w,w+1,\ldots)})$ is the law of motion (conditional distribution) of the state vector in period $w+j$ with density, $d\Psi_{d(w+j)}(\delta_{w+j} \mid \delta_w, a_{d(w,w+1,\ldots)})$;
- $\mathbb{C}_w$ is the set of released DVDs and $\Xi_w$is the set of potential entrants in week w.

5.2. Studio Objective Function

To capture the resulting heterogeneity in studios' objective functions, we model ex post payoffs from releasing DVD d in week t to studio (firm) f as below (see Section 6 for details):

$$\pi^{post}_{fd}(\varphi, t, x_d, p_d, \delta_s, v_d) = \underbrace{\sum_{s\in S} \varphi_{fsdt}\, rev^{post}_{ds}(t, x_d, p_d, \delta_s)}_{\text{Common Knowledge}} + \underbrace{v_{dt}}_{\substack{\text{Private}\\ \text{Information}}}, \qquad (6)$$

where $rev^{post}_{ds}(t, x_d, p_d, \delta_s)$ is the (discounted) ex post revenue of DVD d from segment s. Following Gallant et al. (2018), we assume a weekly discount factor corresponding to an internal rate of return of 20% over the planning horizon. As sales of DVDs 13 weeks after release are (on average) 4% of sales in the first week after release (see Figure 3), we use the discounted sales from the first 13 weeks after release to capture segment-specific DVD revenues:

$$\pi^{post}_{fd}(\varphi, t, x_d, p_d, \delta_s, v_d) = \underbrace{\sum_{s\in S} \varphi_{fsdt} \sum_{j=t}^{t+12} r^{j-t} p_{dj} q_{dsj}(t, x_d, p_{dj}, \delta_{sj})}_{\text{Common Knowledge}} + \underbrace{v_{dt}}_{\substack{\text{Private}\\ \text{Information}}}, \qquad (7)$$

where $q_{dsj} = mktsh_{dsj} M_j$ is the expected quantity of DVD d purchased by segment s in week j.

5.3. Description of the Game

Studios compete in a repeated game of incomplete information. Each week, studios simultaneously decide the DVD release date of movies that have ended a period of exclusive theatrical distribution (eight weeks after theatrical release), within a finite planning horizon (26 weeks after theatrical exclusivity). Studio release choices are final. The ex post payoff in Equation (7) reflects the information set at the end of the game. The first component contains variables that are common knowledge, while the second component contains private information. Studio beliefs on future prices (μ_{pd}) reflect the observed conditional distribution of prices. Studio beliefs on the evolution of the state vector $(\{\Psi_{d(w+j)}\}_{j=1}^{38})$ are consistent with rational play and the information set at the time of decision making.

The state vector is composed of four elements (given our findings of two consumer segments): the two segment-specific inclusive values of the choice set of DVDs $(\mathbb{C}_w)$ and the two segment-specific inclusive values of the set of potential entrants (Ξ_w). In the GEV RUM model, the inclusive value accounts for the impact of rivals' actions on demand. The inclusive value is an aggregative statistic in the release timing game as it allows for a computation of payoffs, without further knowledge of rivals' actions (see Gowrisankaran et al. 2010, Schiraldi 2011, Nevo and Rossi 2010). The inclusive values account for (a) heterogeneous seasonally varying consumer preferences, (b) differentiation across products in several attributes including freshness, and (c) seasonally varying release strategies. The inclusive value of prior DVD releases reflects current competition. The inclusive value of the current entrants reflects anticipated competition in future periods. Thus, the inclusive values parsimoniously capture high dimensionality attribute space. Let *FS* represent the freshness-sensitive segment and *FI* represent the freshness-insensitive segment. The state vector is

$$\delta_w = \left\{\log\left(\sum_{i\in\mathbb{C}_w} \exp(u_{iFSw})\right), \log\left(\sum_{i\in\mathbb{C}_w} \exp(u_{iFIw})\right), \log\left(\sum_{i\in\Xi_w} \exp(\mathbb{E}u_{iFSw})\right), \log\left(\sum_{i\in\Xi_w} \exp(\mathbb{E}u_{iFIw})\right)\right\}. \qquad (8)$$

The state vector evolves as a first-order time-nonhomogeneous Markov process. $\Psi_{d(w+1)}(\delta_{w+1} \mid \delta_w, a_{d(w,w+1,\ldots)})$ describes the conditional distribution (transition kernel) of the state vector in week $w+1$ given the state vector in week w and the release decision of DVD d. In the release-timing game, there are two sources of time nonhomogeneity. First, the inclusive value of current period entrants evolves as a first-order time-nonhomogeneous Markov process, reflecting a (time-nonhomogeneous) MPE in theatrical release dates. Second, the DVD-release-timing policy function is time-nonhomogeneous Markov. We limit both the endogenous and exogenous components of the transition kernel to being periodic (time nonhomogeneous) with year-specific discontinuities. Studio beliefs on the distribution of the state vector in period $w+j$ are described by the iterated Markov kernel denoted by $\Psi_{d(w+j)}(\delta_{w+j} \mid \delta_w, a_{d(w,w+1,\ldots)})$, $j = 2, \ldots, 38$.[5] By the Chapman–Kolmogorov equation, the density of the iterated Markov kernel is defined recursively:

$$d\Psi_{d(w+i+1)}(\delta_{w+i+1} \mid \delta_w, a_{d(w,w+1,\ldots)}) = \int d\Psi_{d(w+i+1)}(\delta_{w+i+1} \mid \delta_{w+i}, a_{d(w,w+1,\ldots)}) \cdot d\Psi_{d(w+i)}(\delta_{w+i} \mid \delta_w, a_{d(w,w+1,\ldots)}), \quad \text{for } i = \{1, \ldots, 37\}. \qquad (9)$$

In our model, private information reflects the idiosyncratic inclination of a studio to favor a release date (or not releasing the movie on DVD) for a focal movie. That is, private information pertains to the match, conditional on observables, between a candidate release date, and the specific DVD. Hence, accounting for the revenue implications of a DVD's attributes, private information reflects the idiosyncratic inclination of a studio to favor a release date (or not releasing the movie on DVD) for a focal movie. For example, in setting release dates, studio may factor in the calendar availability of the actors and the director of the movie to appear on talk shows to generate interest in the movie. This information is unlikely to be available to, or factored into the calculations of, other studios.

We model private information on payoffs from release dates and from the outside option of not releasing the movie on DVD. These are distributed i.i.d. Gumbel. Studios learn their private information for all weeks of the planning horizon at the time of setting DVD release dates when a movie has ended its period of theatrical exclusivity. The distribution of private information is common knowledge. The evolution of the state vector is conditionally independent (given player actions and the current state) of private information. These assumptions are common in the empirical literature as they lead to a tractable form for the equilibrium distribution of the strategic choices in a game (c.f. Srisuma 2013, p. 553). The assumption is reasonable in our context since the movie attributes are highly informative and seasonality plays a focal role in the release-timing game. However, if studios' private information were correlated rather than independent, the model would also need to account for signaling and learning.

To investigate cannibalization, we conduct the following analysis. For all pairs of DVDs, we regress the period between DVD release dates on a dummy indicating if the movie belonged to the same studio (see Table 3). If studios act to avoid cannibalization, two DVDs from the same studio, on average, will have release dates that are further apart than two DVDs from different studios. However, despite considerable statistical power, the test is unable to reject the null. Therefore, the data suggests that studios do not account for cannibalization when making DVD release decisions. This supports our empirical model that abstracts from cannibalization.

Table 3. Time Between DVD Release Dates of Movies ($N = 328{,}454$)

	Coeff.	S.E.
Intercept	104.41***	0.14
Same studio	0.04	0.35

Note. Coeff., coefficient; S.E., standard error; all tests two sided.
***$p < 0.01$.

5.4. Time-Nonhomogeneous MPE

We focus on pure strategy equilibria since they are observationally equivalent to mixed strategy equilibria.[6] A strategy is a function of common knowledge and private information to a specific action (release date), denoted by $a_{d(w,w+1,\ldots)}$. For example, for a focal DVD d that enters the release timing game in week w, a strategy (σ_d), given common knowledge and private information, is

$$\sigma_d(\mathrm{x}_d, \mu_{pd}, \delta_w, \nu_d) = a_{d(w,w+1,\ldots)}. \tag{10}$$

The best response function, denoted by BR_d, maps rivals' strategies (denoted by σ_{-d}) to the strategy that maximizes the player's payoffs. As the actions of rivals are described by the iterated kernel, the best response strategy to σ_{-d} can be written as the best response strategy to $\{\Psi_{d(w+j)}\}_{j=1}^{38}$, the iterated kernel formed by σ_{-d}:

$$\begin{aligned} &BR_d(\varphi, \mathrm{x}_d, \mu_{pd}, \sigma_{-d}, \delta_w, \nu_d) \\ &\quad = BR_d\left(\varphi, \mathrm{x}_d, \mu_{pd}, \{\Psi_{d(w+j)}\}_{j=1}^{38}, \delta_w, \nu_d\right). \end{aligned} \tag{11}$$

Define ex ante revenues, $rev_{ds}^{ante}(j, x_d, \mu_{pd}, \Psi_{d(w+j)}, \delta_w, a_{d(w,w+1,\ldots)})$, to be the expected revenue of DVD d from segment s in a future period j (where w is the week DVD d enters the release-timing game and $a_{d(w,w+1,\ldots)}$ identifies $w+t$, the week a movie is released on DVD):

$$\begin{aligned} &rev_{ds}^{ante}(j, x_d, \mu_{pd}, \Psi_{d(w+j)}, \delta_w, a_{d(w,w+1,\ldots)}) \\ &\quad = \int\int p_{dj} q_{dsj}(t, x_d, p_{dj}, \delta_{w+j})\, d\mu_{pd}(x_d, \delta_{w+j}) \\ &\quad\quad \cdot d\Psi_{d(w+j)}(\delta_{w+j} \mid \delta_w, a_{d(w,w+1,\ldots)}). \end{aligned} \tag{12}$$

The ex ante payoffs to studios from releasing the DVD d in a future period t, net of private information (υ_{dt}), are

$$\begin{aligned} &\pi_{fd}^{ante}(\varphi, t, x_d, \mu_{pd}, \{\Psi_{d(w+j)}\}_{j=1}^{38}, \delta_w) \\ &= \sum_{s\in S} \varphi_{fsdt} \sum_{j=t}^{t+12} r^j rev_{ds}^{ante}(j, x_d, \mu_{pd}, \Psi_{d(w+j)}, \delta_w, a_{d(w,w+1,\ldots)}). \end{aligned} \tag{13}$$

The best response strategy for the DVD d (that enters the game in week w) is

$$\begin{aligned} &BR_d\left(\varphi, \mathrm{x}_d, \mu_{pd}, \{\Psi_{d(w+j)}\}_{j=1}^{38}, \delta_w, \nu_d\right) \\ &= \underset{0<t<27}{\arg\max}\left\{\pi_{fd}^{ante}(\varphi, t, x_d, \mu_{pd}, \{\Psi_{d(w+j)}\}_{j=1}^{38}, \delta_w) + \upsilon_{dt}, 0\right\}. \end{aligned} \tag{14}$$

At equilibrium, actors play the best response strategy to the strategies of their rivals. Let σ_d^* denote equilibrium strategies. Then,

$$\begin{aligned} \sigma_d^* &= BR_d(\varphi, \mathrm{x}_d, \mu_{pd}, \sigma_{-d}^*, \delta_w, \nu_d) \\ &= BR_d\left(\varphi, \mathrm{x}_d, \mu_{pd}, \{\Psi_{d(w+j)}^*\}_{j=1}^{38}, \delta_w, \nu_d\right), \quad \forall d, \end{aligned} \tag{15}$$

where $\{\Psi^*_{d(w+j)}\}_{j=1}^{38}$ are rational beliefs on future states due to the equilibrium strategies (σ^*_{-d}) of rivals.

A studio observes only its own private information. The expectation of a player's strategy with respect to its private information shocks is the ex ante (prior to the studio learning its private information) probability of the player's actions, given common information and rivals strategies. For any set of rival strategies, the best response strategy implies a corresponding ex ante best response probability. The ex ante equilibrium probability is the expectation of the best response strategy with respect to the private information, given the iterated kernel corresponding to equilibrium rivals' strategies. Specifically, the equilibrium probability that DVD d is released corresponding to the action $a_{d(w,w+1,\ldots)}$ is given by

$$\begin{aligned}\Pr^*_d(a_{d(w,w+1,\ldots)}) &\\ = \int 1\big(BR_d(\varphi, x_d, \mu_{pd}, \{\Psi^*_{d(w+j)}\}_{j=1}^{38}, \delta_w, \nu_d) &\\ = a_{d(w,w+1,\ldots)}\big)\, d\nu, &\quad (16)\end{aligned}$$

where 1( ) is the indicator function. The ex ante equilibrium release probabilities ($\Pr^*_d$) span a convex compact subset of the Euclidean space and are continuous with respect to rival's equilibrium release probabilities. Brouwer's fixed-point theorem implies that a fixed point (an MPE) exists. Firms' beliefs over the state vector are then perfect Bayesian: the anticipated conditional distribution of states in future periods is consistent with equilibrium play, given the current state of the game.

5.5. Estimating the Release-Timing Model

We adapt the estimation strategy of conditional choice probability (CCP) estimators (Bajari et al. 2007, Arcidiacono and Miller 2011), to the release-timing game. Conditional on the equilibrium played in the data, CCP estimators recover and model the best responses of individual players. From (16), the likelihood of a seeing a movie d that entered the game in week w being released on DVD in $w+t$ is given by

$$\begin{aligned}&\mathcal{L}_{fd}(t, x_d, \hat{\mu}_{pd}, \{\hat{\Psi}_{d(w+j)}\}_{j=1}^{38}, \delta_w; \varphi)\\ &= \frac{\exp(\pi^{ante}_{fd}(\varphi, t, x_d, \hat{\mu}_{pd}, \{\hat{\Psi}_{d(w+j)}\}_{j=1}^{38}, \delta_w))}{1+\sum_{k=1}^{26}\exp(\pi^{ante}_{fd}(\varphi, k, x_d, \hat{\mu}_{pd}, \{\hat{\Psi}_{d(w+j)}\}_{j=1}^{38}, \delta_w))}, \quad (17)\end{aligned}$$

where $\langle \hat{\mu}_{pd}, \{\hat{\Psi}_{d(w+j)}\}_{j=1}^{38}\rangle$ are empirical analogs of the equilibrium distributions, recovered as described in Appendix B.

6. Competition in the U.S. DVD Industry

We first estimate a baseline model in which studios equally weight revenues from different consumers and different movies. We parameterize possible drivers of managerial conservatism in managers' objective function. Therefore, in addition to the baseline model, we sequentially estimate the following models to capture potential dimensions of managerial conservatism:

(a) *Consumer segments*: Given the consumer segment differences in responsiveness to prior theatrical revenues, we first test if the studios focus more/less on different consumer segments as suggested by managerial conservatism. We estimate a model where the weights vary by segment but not by studio. We find that the data supports a difference in weights across the segments (the likelihood ratio test rejects the null, $p < 0.05$).

(b) *Movie studios*: As studios are heterogeneous, we test if our prior findings vary by studio. We estimate a model where the weights vary by both segment and studio. The data support a differential consumer focus by studio (the likelihood ratio test rejects the null, $p < 0.05$).

(c) *Time*: There may have been changes in managerial behavior over time. Therefore, we estimate the following models. (1) Weights vary by studio and by time (in the first versus the second half of the data period). (2) Weights vary by studio and consumer segment, and by time (in the first versus the second half of the data period). (3) Weights vary by consumer segment and annually. (4) Weights vary by studio, consumer segment, and annually. In all four cases, we find that the data do not support time-varying weights (in all four cases, the likelihood ratio test does not reject the null, $p > 0.1$).

(d) *Movies*: A movie's prior theatrical success is likely to influence managerial (and investor) expectation of DVD success—movies that did well in the theatrical channel might well be expected to do well in DVD channels. Therefore, we estimate three models where segment weights vary across movies as a linear, quadratic, and cubic function of theatrical revenues. We find that the data supports a model where weights vary as a quadratic function of theatrical revenues. The likelihood ratio test rejects the null when testing against simpler models (both where weights are symmetric across movies and where weights vary as a linear function of theatrical revenues, $p < 0.05$). However, the likelihood ratio does not reject the null when testing the model where weights vary as a cubic function of theatrical revenues ($p > 0.1$).

(e) *Interaction*: We estimate three models where segments weights vary as a quadratic function of theatrical revenues interacted with fixed effects indicating the studio, the first versus the second half of the data period, and the year. In all cases, the data does not support the model additions: the likelihood ratio test does not reject the null ($p > 0.1$).

Our findings (Table 4 reports model estimates) suggest that studios focus on consumers who are more

Table 4. Release Timing Model Estimates ($N = 730$)

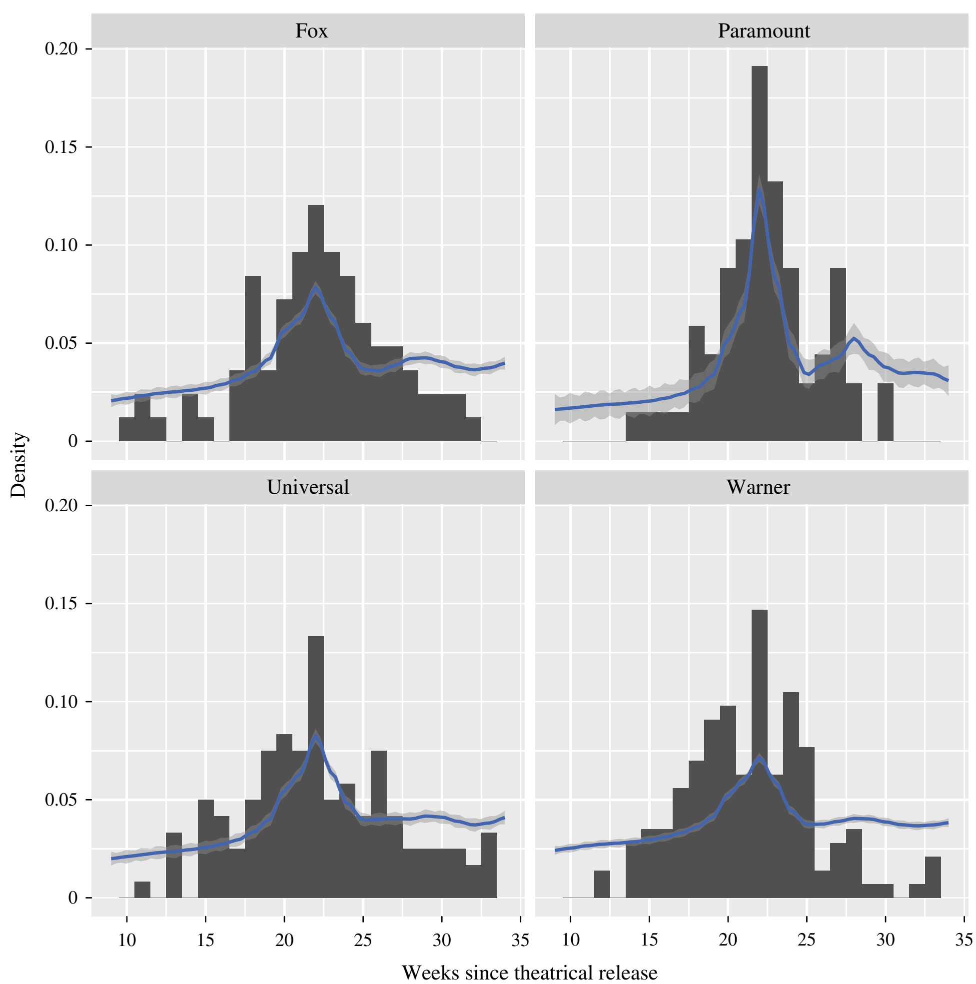
	Studios	Coeff.	S.E.
Freshness-sensitive segment	Theatrical revenue	-8.21^{***}	(2.12)
	(Theatrical revenue)^2	14.28^{***}	(5.34)
	Columbia	0.61^{**}	(0.24)
	Disney	1.09^{***}	(0.25)
	Fox	0.95^{***}	(0.20)
	Paramount	1.31^{***}	(0.29)
	Universal	1.15^{***}	(0.19)
	Warner	0.97^{***}	(0.21)
	Other studios	2.07^{**}	(0.70)
Freshness-insensitive segment	Theatrical revenue	-5.10	(3.12)
	(Theatrical revenue)^2	8.04	(8.52)
	Columbia	1.04^{***}	(0.30)
	Disney	1.31^{***}	(0.36)
	Fox	1.13^{***}	(0.26)
	Paramount	2.69^{***}	(0.40)
	Universal	1.41^{***}	(0.28)
	Warner	1.21^{***}	(0.26)
	Other studios	2.32^{*}	(1.19)

Note. Coeff., coefficient; S.E., standard error; all tests two sided.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

box-office sensitive, and focus more on the revenue considerations of larger than smaller (by prior theatrical revenue) movies. Figure 8 provides a visual summary of the fit of our model by comparing the observed and predicted densities of time between theatrical and DVD release dates.[7] Note that the model provides a reasonable fit. Importantly, note that the model accounts for the firm asymmetries in release strategies (for example, compare the release strategies of Paramount and Warner).

As mentioned earlier, a limitation in the current empirical literature on conservatism is that estimation has used approaches that do not provide insights in to drivers of managerial conservatism. For example, Einav (2010) estimates studios optimizing regular maximands and finds excessive crowding in peak release weekends. He interprets this crowding as consistent with conservative equilibria. Therefore, he is unable to simulate alternative equilibria since there are no structural parameters governing the conservative

Figure 8. (Color online) Observed and Fitted Density of Weeks Between Theatrical and DVD Release



Notes. Histogram of the observed distribution of weeks between theatrical and DVD release by studio. Overlay of the fitted probability and associated standard errors.

Table 5. Expected Revenue in the Conservative Equilibrium and Revenue Maximization ($N = 730$)

	Δ DVD revenue	
	Coeff.	S.E.
Theatrical revenue	-7.62^{***}	(0.70)
(Theatrical revenue)^2	6.89^{***}	(2.26)
Columbia	0.14^{***}	(0.05)
Disney	0.32^{***}	(0.05)
Fox	0.08	(0.06)
Paramount	0.38^{***}	(0.06)
Universal	0.19^{***}	(0.05)
Warner	0.19^{***}	(0.05)
Other studios	0.25^{***}	(0.10)
R^2	0.48	

Note. "Δ DVD revenue" denotes difference in DVD revenue between the conservative equilibrium and revenue maximization; Coeff., coefficient; S.E., standard error; all tests two sided.

$^{***}p < 0.01$.

equilibrium. Other studies (Ravid 1999, Basuroy et al. 2003) have used reduced-form approaches. In contrast, an advantage of our structural approach is the ability to conduct counterfactuals of alternative equilibria.

We adopt the approach advocated by Aguirregabiria and Ho (2012) to recursively compute the equilibrium release probabilities corresponding to both the observed equilibrium and one specific alternative equilibrium—revenue maximization—as it is the default equilibrium estimated in the majority of the structural industrial organization literature. Specifically, we first compute release strategies conditional on the observed (probability of) play of competitors. In successive iterations, we use the computed release strategies in the prior iteration, to update the probability of play of all competitors and recompute release strategies (we describe the steps of the algorithm in Appendix C). The counterfactual thus accounts for the endogenous evolution of play with changes in policy.

Table 5 reports the results of the following regression. The dependent variable is the difference in expected DVD revenues corresponding to the observed equilibrium and revenue maximization. The explanatory variables are the linear and quadratic terms of theatrical revenues, and studio dummies. We find that the observed equilibrium leads to higher expected DVD revenues for larger movies but lower expected DVD revenues for smaller movies. This is as expected since there is a greater weight on revenues from larger movies. Note though this result is despite the weight on freshness-sensitive customer segment, which could also benefit small movies (if they are released while fresh).

Next, we analyze these findings of greater revenues of bigger movies by relating them to release timing decisions. We tabulate the expected number of releases in Thanksgiving, the largest peak demand period in the DVD market, by number and size of movie (see Table 6). For the top three quartiles of movies, the observed equilibrium results in more movies and larger movies released in this peak demand period than in revenue maximization equilibrium. For the bottom size quartile, fewer and smaller movies are released in the observed equilibrium compared to revenue maximization equilibrium. Overall, in this peak demand period, more and larger movies are released in the observed equilibrium compared to a revenue maximization equilibrium. This result is similar to Einav's finding of more crowded peak demand weeks in theatrical release. Our additional result of peak weeks being more crowded with bigger movies comes from parameterizing conservative equilibria (i.e., allowing movie and segment weights in objective function). Relating these findings to the ones in the previous paragraph, the observed release strategies increase DVD revenues of larger movies at the expense of the DVD revenues of smaller movies.

We now turn our attention to freshness sensitivity and its impact on release dates and revenues of movies. Freshness sensitivity lowers incentives of studios to delay DVD release until a seasonal peak. Hence, freshness sensitivity reduces the number of releases in peak weeks (i.e., more DVDs are likely released closer to their theatrical release dates). However, in the competitive release timing game, lower crowding in peak weeks increases the incentives of studios to wait for a peak week, in turn increasing the number of releases (crowding) in peak weeks. Hence, it hard to predict a priori the net effect of freshness sensitivity on equilibrium release

Table 6. Summary Statistics of Expected DVD Releases in the Thanksgiving Period

Theatrical revenue	Equilibrium	Number of DVDs released	Total theatrical gross of DVD releases
Highest quartile	Conservative	1.90	304.2
Highest quartile	Revenue maximization	1.78	285.2
Second-highest quartile	Conservative	1.52	92.6
Second-highest quartile	Revenue maximization	1.47	89.9
Second-lowest quartile	Conservative	1.58	51.6
Second-lowest quartile	Revenue maximization	1.38	45.8
Lowest quartile	Conservative	1.54	26.3
Lowest quartile	Revenue maximization	1.58	27.2

Note. Movies classified by prior theatrical revenues into quartiles; "Number of DVDs released" denotes expected number of new DVDs released; "Total theatrical gross of DVD releases" denotes expected total prior theatrical gross of new DVD releases, in millions of U.S. dollars.

Table 7. Impact of Freshness on DVD Revenue ($N = 730$)

	Δ DVD revenue	
	Coeff.	S.E.
Theatrical revenue	−32.60***	(3.25)
(Theatrical revenue)^2	72.38***	(10.50)
Columbia	−0.95***	(0.21)
Disney	−1.10***	(0.23)
Fox	−3.30***	(0.26)
Paramount	−1.96***	(0.29)
Universal	−2.96***	(0.24)
Warner	−2.25***	(0.21)
Other studios	−1.98***	(0.44)
R^2	0.76	

Note. "Δ DVD revenue" denotes difference in DVD revenue between as observed (consumers with observed consumer preferences) and if all consumers were freshness-insensitive; Coeff., coefficient; S.E., standard error; all tests two sided.

***$p < 0.01$.

dates and revenues (of large and small movies). Therefore, we conduct the following analysis. We simulate DVD revenues given freshness-insensitive consumers.[8] Table 7 reports the results of a regression where the dependent variable is the difference in the expected DVD revenues from consumers with observed preferences and if all consumers were freshness insensitive. The independent variables are a quadratic function of prior theatrical revenues and studio dummies. We find that for smaller movies, freshness sensitivity decreases revenues. For larger movies, the converse is true: freshness sensitivity increases expected revenues. This is because freshness sensitivity reduces crowding (relative to equilibrium release dates given freshness-insensitive consumers) in peak weeks; this disproportionately benefits larger movies.

Summarizing, our analysis from estimation and simulations finds the following: conservatism manifests itself via larger coefficients on revenues from larger movies and revenues from freshness-sensitive customers. The net result of the two weights is more crowding in peak periods (the weight on larger movies increases crowding, the weight on freshness decreases crowding). These strategies increase the revenues of larger movies at the expense of (resultantly lower) revenues of smaller movies.

7. Conclusion

We develop a modeling framework to measure heterogeneous consumer preferences and marketing-mix decisions in a dynamic competitive environment. We examine the DVD market in the United States with this modeling framework. We find two distinct consumer segments with different (seasonal, freshness, and other product attribute) preferences. Studios pay more attention to the DVD release dates of movies that were more successful prior in theatres. This evidence is consistent with previous studies of managerial conservatism in this industry. Beyond this specific application, our model of competition can be adapted to study competition in other contexts where the timing of new products depends on the preferences of multiple customer segments and the competitive jockeying among rivals.

Our model has some limitations that may be binding in other applications. First, a model where competing firms optimize by portfolio (i.e., across all products) rather than by individual product may be a better description of reality. However, in a market with heterogeneous products (in our application, movies differ on several attributes), portfolio optimization leads to a significant expansion of the action and state space. Therefore, the extant empirical literature has typically abstracted from this concern (see Hollenbeck 2017 and Sweeting 2013 for similar assumptions). Another important feature of our industry that simplifies the computation of our model is stable DVD prices after release. In other applications, our model can be extended to consider time-varying prices after release. Finally, our model can also be extended to products with different "versions" of products (for example, hard copy and soft bound books, or free/basic products with paid upgrades). In each of these, researchers are likely to be limited by the current state-of-the-art in statistical and computational toolkits. However, we remain optimistic that advances in technology will lead to new research opportunities.

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Appendix A. Algorithm for Estimating the Demand Model

1. To compute market shares in any week, we assign equal purchase probabilities across segments in the 12th week of 2000 (the week before the first week of data used in the market-share model). In subsequent weeks, we use the law of total probability to construct the fraction of consumers in segment A, purchasing a DVD in week w:

$$F_{s(w+1)} = F_{sw} \sum_{d \in \mathbb{C}_w} \frac{\exp(u_{dsw}(D_{sw}=1))}{1 + \sum_{i \in \mathbb{C}_w} \exp(u_{isw}(D_{sw}=1))} + (1 - F_{sw}) \sum_{d \in \mathbb{C}_w} \frac{\exp(u_{dsw}(D_{sw}=0))}{1 + \sum_{i \in \mathbb{C}_w} \exp(u_{isw}(D_{sw}=0))}, \quad \text{(A.1)}$$

where F_{sw} denotes the proportion of the consumers in a segment that purchased a DVD in the week prior to w—i.e., in week $w-1$, $\mathbb{C}_w$ denotes the set of DVDs available for purchase in week w, $u_{dsw}(D_{sw}=1)$ is the utility from purchasing DVD d to a consumer in segment s who purchased a DVD in the preceding period (i.e., $w-1$), and $u_{dsw}(D_{sw}=0)$ is the utility from purchasing DVD d to a consumer in segment s who did not purchase a DVD in the preceding period (i.e., $w-1$).

2. We use the contraction map $(u_{dAw})_{n+1} = (u_{dAw})_n + \log(mktsh'_{dw}/mktsh_{dw})$ to recover u_{dAw}, the utility to a consumer in segment A from DVD d in week w. $mktsh'_{dw}/mktsh_{dw}$ is the ratio of the measured share to the computed share of DVD d in week w (aggregated across all segments). Coefficients of the utility of the segment A are recovered from the fixed points of the contraction, while segment differences in heterogeneous parameters are recovered as parameters in an outer loop.

3. We estimate the model using the generalized method of moments (see Berry et al. 1995). We first assume that the errors are homoscedastic to arrive at a consistent estimator of the parameters. In a second step, we use the first-stage estimates to recover a variance matrix that allows for both intraweek correlation and heteroscedasticity, and reestimate the model. Clustering standard errors by week allows residual week-specific demand shocks, beyond seasonal controls, to be common across DVDs in a week.

4. To maintain tractability, we sequentially test for the appropriate number of model components. Following Livera et al. (2011), we add spectral components until additional components are not significant. Next, we increase the number of segments in the model. Following Soysal and Krishnamurthi (2012), as the N segment model is nested in the $N+1$ segment model, the joint significance of the class allocation probabilities in the $N+1$ segment model is a test of model specification.

5. To accelerate the rate of convergence of the fixed-point algorithm, we use rank-reduced extrapolation, as discussed by Varadhan and Roland (2008). Acceleration schemas are operators from a (globally convergent) contraction map to a (globally convergent) contraction map, where the output mapping requires less iteration to convergence. In our experience, all three acceleration algorithms given by Varadhan and Roland (2008) substantially increase the rate of convergence of the stock Berry–Levinsohn–Pakes map, dramatically reducing computational load while preserving global convergence. We use the augmented Lagrangian adaptive barrier minimization algorithm to enforce the constraint that class allocation probabilities must sum to one, and estimate using mathematical programming with equality constraints (see Madsen et al. 2004 for a discussion and Varadhan 2011 for an implementation).

Appendix B. Algorithm for Estimating the Release-Timing Model

1. We estimate the following three equations:

(a) *Mean price of a DVD*:

$$\bar{p}_d = \lambda_{11} + \lambda_{1y} + \sum_{h=1}^{H}\left(\lambda_{1ah}\sin\left(\frac{2\pi hr}{52}\right) + \lambda_{1bh}\cos\left(\frac{2\pi hr}{52}\right)\right) + \lambda_{1x}x_d + \zeta_{1d}, \tag{B.1}$$

where λ_{11} is a segment-specific intercept, λ_{1y} is a year-specific fixed effect, λ_{1ah} and λ_{1bh} are the Fourier coefficients, H is the number of harmonics of the fundamental frequency (corresponding to annual periodicity) included in the model, w is the week the movie was released in theaters, r is w modulo 52, and y is the year to which w corresponds. λ_{1x} is a vector of coefficients and fixed effects corresponding to the attributes of the movie (x_d). ζ_{1d} is the error term.

(b) *Freshness of a DVD*:

$$WB_d = \lambda_{21} + \lambda_{2y} + \sum_{h=1}^{H}\left(\lambda_{2ah}\sin\left(\frac{2\pi hr}{52}\right) + \lambda_{2bh}\cos\left(\frac{2\pi hr}{52}\right)\right) + \lambda_{2x}x_d + \zeta_{2d}, \tag{B.2}$$

where λ_{21} is a segment-specific intercept, λ_{2y} is a year-specific fixed effect, and λ_{2ah} and λ_{2bh} are the Fourier coefficients. λ_{2x} is a vector of coefficients and fixed effects corresponding to the attributes of the movie (x_d). ζ_{2d} is the error term.

(c) *Weekly price of a DVD*:

$$p_{dw} = \lambda_{31} + \lambda_{3y} + \sum_{h=1}^{H}\left(\lambda_{3ah}\sin\left(\frac{2\pi hr}{52}\right) + \lambda_{3bh}\cos\left(\frac{2\pi hr}{52}\right)\right) + \sum_{j=1}^{4}\lambda_{3\delta j}\delta_{jw} + \lambda_{3x}x_d + \lambda_{3WB}\log(WB_d) + \lambda_{3WR}\log(WR_{dw}) + \zeta_{3d}, \tag{B.3}$$

where λ_{31} is a segment-specific intercept, λ_{3y} is a year-specific fixed effect, λ_{3ah} and λ_{3bh} are the Fourier coefficients, and $\lambda_{3\delta j}$, $j \in \{1, \ldots, 4\}$ are the four state vector coefficients. λ_{3x} is a vector of coefficients and fixed effects corresponding to the attributes of the movie (x_d). λ_{3WB} is the coefficient on the number of weeks between theatrical and DVD release and λ_{3WR} is the coefficient on the number of weeks since DVD release. ζ_{3d} is the error term.

2. We construct the inclusive value of entrants each week from the demand estimates, and the expected average price and freshness. The augmented Dickey–Fuller test rejects the null of nonstationarity for all four state variables ($p < 0.01$). We use a vector autoregressive model with exogenous variables (VARX) to track the evolution of the state vector. The Wold theorem implies that under mild regularity conditions, stationary vector time series have a VARX representation. A VARX model allows for a vector of endogenous variables (in our case the state vector) to depend on the lagged values of the endogenous variables and a design matrix of exogenous variables (the exogenous matrix consists of an intercept, the 14 Fourier basis variables, and five year fixed effects). The VARX model is thus a flexible tool to capture the evolution of a multivariate Markov process. The forecasts of the VARX reflects expected states in periods $t+1, t+2, \ldots$ based on the common information in period t (Nijs et al. 2001) and hence provide the empirical analog of $\{\Psi_{d(w+j)}\}_{j=1}^{38}$. Note that the VARX model allows both the inclusive value describing current competitors and the inclusive value of potential entrants to jointly affect each other (both sets of variables are treated as being endogenous in the VARX). The forecast state vector in a period is the equilibrium distribution of the inclusive value of the industry (the aggregative statistic) in a period. We use the distribution of the industry to compute the distribution of prices after entry.

3. Let $\Omega_d = \{\Omega_{dr}: r \in R\}$ be the collection of probabilities, indexed by DVD d, over the set of candidate release dates R. The contribution of each focal DVD in a week to the aggregative statistic is $\sum_{t \le w}\Omega_{dt}\exp(Eu_{dsw}(t))$, where Ω_{dt} is obtained from step 1(b) and $Eu_{dsw}(t)$ is the expected utility from purchasing DVD d to a consumer in segment s in week w, if the

DVD were released on t. Hence, the distribution of the inclusive values of rivals corresponding to freshness insensitive segment is given by

$$\log\left(E\exp(\delta_{1w}) - \sum_{t\le w}\Omega_{dt}\exp(Eu_{dFSw}(t))\right), \qquad \text{(B.4)}$$

where δ_{1w} is the first component of the predicted industry state vector. And the distribution of the inclusive values of rivals corresponding to freshness insensitive segment is given by

$$\log\left(E\exp(\delta_{2w}) - \sum_{t\le w}\Omega_{dt}\exp(Eu_{dFIw}(t))\right), \qquad \text{(B.5)}$$

where δ_{2w} is the second component of the industry state vector.

4. For each week in the planning horizon, we compute the expected revenue for a candidate release date by computing a two-dimensional integral over the distribution of prices after release of the focal DVD and the expected state vector in the period. We use sparse grids quadrature (with 128 nodes) to construct the integral (see Schmedders and Judd 2014, p. 354).

Appendix C. Algorithm for Estimating Equilibrium Revenue in the Counterfactuals

1. For each movie, we compute expected revenues from each candidate release date, holding constant the observed release schedules of competitors, as in step 3 of Appendix B. Let $\Omega_d = \{\Omega_{dr}\colon r \in R\}$ be the collection of probabilities, indexed by DVD d, over the set of candidate release dates R.

2. We compute the expected state variable ($E\delta_w$) as

$$E\delta_w = \left\{\begin{array}{l} \log\left(\sum_{i\in\Xi_w}\sum_{t\le w}\Omega_{it}\exp(Eu_{iFSw}(t))\right) \\ \log\left(\sum_{i\in\Xi_w}\sum_{t\le w}\Omega_{it}\exp(Eu_{iFIw}(t))\right) \\ \log\left(\sum_{i\in\Xi_w}\left(1-\sum_{t\le w}\Omega_{it}\right)\exp(\mathbb{E}u_{iFSw})\right) \\ \log\left(\sum_{i\in\Xi_w}\left(1-\sum_{t\le w}\Omega_{it}\right)\exp(\mathbb{E}u_{iFIw})\right) \end{array}\right\}, \qquad \text{(C.1)}$$

where Ξ_w is the set of movies for which week w is a potential DVD release date, and $Eu_{iFSw}(t)$ and $Eu_{iFIw}(t)$ are the expected utility to the freshness-sensitive and -insensitive segments, respectively, in week w if DVD i were released on t.

3. We derive the laws of motion of the expected state variable as in step 2 of Appendix B and recompute expected revenues from each candidate release date, given beliefs. Let $\Omega'_d = \{\Omega'_{dr}\colon r \in R\}$ be the collection of release probabilities, indexed by DVD d, over the set of candidate release dates R.

4. If $\|\Omega_d - \Omega'_d\| >$ threshold, then we set $\Omega_d = \Omega'_d$ and recompute steps 2 and 3. We use the Euclidean distance (the square root of the sum of squared differences in policy functions across iterations) and set the threshold to be 1e-4. In our application, reducing the threshold further has virtually no effect on our estimates.

Endnotes

[1] Several related aggregation concepts have been studied in the extant literature. Due to differences in game structure across approaches, to the best of our knowledge, there is no accepted definition of an "aggregative game." Jensen (2010) introduces quasi-aggregative games and shows that several prior aggregation concepts can be considered special cases of quasi-aggregative games. Our model very closely corresponds with Jensen's definition of a quasi-aggregative game (see Jensen 2010, Definition 1, p. 47). However, while Jensen describes a game of complete information, we consider a game of incomplete information. Jensen uses the term "quasi" to emphasize that functions (see Jensen 2010, pp. 47–48) in his framework are only determined up to monotonic transformations. As we specify the inclusive value from the demand model as being the aggregator function, we henceforth refer to the release-timing model as an aggregative game.

[2] For parsimony, we do not list all arguments of the utility function (for example, freshness and price) when describing the demand model. In the release-timing game, as candidate release dates correspond to different freshness and price, we explicitly list these arguments of the market-share function.

[3] http://www.imdb.com (accessed July 21, 2014).

[4] Aggregate choice models typically embed single discreteness, rather than multiple discreteness, models in the calculation of the aggregate choice probabilities. A researcher's choice of models is limited by data as estimating multiple discreteness models requires disaggregate data, which is not feasible in many applications (including ours). Further, as multiple discreteness models operate on bundles of choices rather than individual choices, the computational mechanics of the multiple discreteness model scale as a polynomial function of the number of choices (see Bento et al. 2009, pp. 679–680 for a discussion). Thus, even with access to disaggregate data, researchers often use single discreteness models to avoid the computational burden that accompanies the estimation of a multiple discreteness model on a large choice set (as in our application).

[5] A studio holds beliefs over 38 weeks in the future, corresponding to the 26 weeks of the planning horizon and an additional 12 weeks to account for revenue, and hence payoffs, after DVD release.

[6] Milgrom and Weber (1985) show that in incomplete-information games, if players' informational variables have an atomless distribution, mixed strategies are empirically indistinguishable from pure strategies. In such games, every mixed strategy has a purification: "a pure strategy equilibrium at which each player has the same expected payoff and the same distribution of observable behavior as at the mixed strategy equilibrium in each of his informational states" (Milgrom and Weber 1985, p. 619). Further, note that by construction, studios are, almost surely, never indifferent between two actions (also see Aguirregabiria and Mira 2007, p. 8, footnote 3).

[7] In the interest of readability, the figure focuses on the smallest studio (Paramount), two studios that are representative of the average, and the largest studio (Warner) by movie output.

[8] We set the freshness-sensitivity coefficient of all consumers to zero. Further, we model studios as maintaining their measured objective functions, corresponding to a situation of studios persisting in their beliefs due to a lack of learning as they decide their release strategies.

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