Profitably Bundling Information Goods: Evidence from the Evolving Video Library of Netflix

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Abstract

Using a unique dataset of the Netflix video on demand library, this article measures the characteristics of information goods important for strategically employing a mixed bundling strategy. By matching the titles entering and exiting the library to their relevant properties, I use a characteristic approach to determine when the value to Netflix of adding a title exceeds the licensing fee and when the displacement effect associated with a presence in the library dictates that the title will be offered only as a pure component. Results show that new products are more profitable to bundle, but are offered for shorter lengths of time, and that titles of median commercial success are bundled more frequently than the most and least successful. The number of similar films exiting the library is important to how likely a film is to enter, indicating strategic bundling. These results are generalizable to the streaming video industry and any information goods with rapidly diminishing marginal utility.

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1 Introduction

In 2007 Netflix began a streaming video service as a complement to the established DVD-by-mail rental option. Customers were originally able to watch the number of hours from a limited library equal to the dollar total they spent each month. This strategy greatly limited the scope of the instant viewing program, and the intention was always to expand the potential of unlimited video on demand (VOD) delivered through an internet connection. Beginning in early 2008, after a substantial investment in the video library and streaming service Netflix provided its unlimited instant service for no additional charge to all paying DVD customers.[1] Since that time Netflix has separated the streaming and DVD services completely, and competitors Amazon and Hulu have launched premium services with similar bundled streaming VOD models. The rise of a bundled video subscription has coincided with the decline in physical video rentals, but it is unclear what content makes this bundle profitable, and therefore to what extent streaming video will supplant the pay-per-use rental. In this paper I examine the bundled offering of Netflix in order to empirically examine what characteristics of an information good make mixed bundling feasible.

The digital video market is supplanting the physical market in the United States. Where once videos were commonly rented through brick-and-mortar rental stores, and discs purchased in large quantities, consumers are rapidly moving to digital delivery of both rental and purchasing. In fact, 2014 was the first year in which American spent more on digital video than physical discs for filmed content.[2] Netflix offers most new releases in single offerings through a physical DVD service, and a mixed bundle of a subset of these offerings through unlimited VOD. Anecdotal evidence seems to indicate that the unlimited streaming services must avoid the large, blockbuster films and replace them with a wide range of documentaries, smaller movies, television shows, and only the occasional huge commercial success. The appropriate bundled offerings allow Netflix to use the less expensive long tail of programming to achieve necessary consumer utility while keeping costs low enough to maintain the streaming model.

A considerable amount of research has questioned when bundling is profitable. Price discrimination research, such as Stigler (1963); Adams and Yellen (1976) suggests that bundling may allow consumers to take advantage of heterogeneous willingness to pay among consumers. More recent extensions include McAfee et al. (1989) providing conditions for when mixed bundling is profitable, Chu et al. (2011) including bundling pricing, and Chen and Riordan (2013) establishing general conditions for the profitability of

[1] http://www.sfgate.com/cgi-bin/article.cgi?f=/n/a/2008/01/13/financial/f090113S93.DTL Accessed: 10/08/2013.

[2] http://www.ibtimes.com/home-entertainment-2014-us-dvd-sales-rentals-crater Accessed: 03/11/2015.

bundling negatively dependent products. Following the work of Crawford (2008) I add to the empirical research into the motivation to bundle by analyzing the characteristics of titles Netflix provides in a mixed bundle and comparing those products to the offerings of pure components. Derdenger and Kumar (2013) have found mixed bundling to be profitable through what they call "dynamic consumer segmentation," a result similar to that observed in this paper.

Netflix services were separated into physical and streaming delivery in 2011, isolating streaming as an avenue to expand on its own.[3] The delivery of streaming video has been untethered from a computer, allowing streaming through many devices such as video game consoles, and potentially being added to cable television boxes in the near future.[4] In addition to the technical changes, the library of offerings on VOD is constantly changing. Licensing contracts with significant rights owners are created, renewed, and allowed to expire, creating an ever-shifting set of videos available in the library. Beyond the licensing of already established works, Netflix has ventured into content creation. Working primarily in television, Netflix has created and resurrected critically acclaimed series to add to its library.[5]

During the sample period there was a mixed bundle of services offered by Netflix, the pure components of a physical DVD rental and the bundle of a streaming video library. With physical rental, consumers pay a single monthly fee but are limited by the number of movies they receive at any time. The consumer may choose any film in the physical library but is not able to access all in a bundle. In buying the bundle there is also a monthly fee, but the fee allows consumers to access the entire VOD library at any time. The library contains fewer titles than physical rentals, but the amount viewed is only restricted by internet connection and time. The standard subscription plan also allows for streaming to occur on two devices simultaneously.

In order to make this a profitable model not all titles are included for this bundle, and the programmers must consider the threshold utility necessary to maintain the customer base while also balancing licensing fees. The realities of major movie releases likely mean that it will never be profitable to have a bundle of all titles. Licensing fees, and the process of "windowing" are designed to maximize profits beyond theatrical release (Nelson et al., 2007; Waterman and Weiss, 2010). The rights holder must consider the potential for displacement of sales from this effect, similar to that found in streaming music by (Hiller, 2014; Aguiar and Waldfogel, 2015).[6] The streaming library must be dynamic in order to

[3]http://news.cnet.com/8301-13506_3-20078765-17/netflix-hikes-prices-adds-dvd-only-plan/ Accessed: 10/08/2013.

[4]http://www.usatoday.com/story/tech/2013/10/14/netflix-cable-boxes/2978901/ Accessed: 10/15/2013.

[5]http://www.wired.com/underwire/2013/03/netflix/?cid=co6594034 Accessed: 10/09/2013.

[6]Displacement with movies has not been proven causally, but anecdotally the rise of streaming video has been correlated with massive decreases in the sales of physical films.

account for these facts. Currently consumers can only watch a small subset of all releases in the bundle, this paper examines what characteristics make that subset profitable, and how the bundle is determined strategically.

Netflix does not have a monopoly on these products, as they are readily available for purchase across numerous outlets. The rights holders of these movies sell rental copies for physical delivery, and only allow inclusion in the streaming bundle if a licensing deal can be reached. Netflix only agrees to pay the licensing fee if the expected profit derived from the marginal utility of consumers from adding the video exceeds that of any other possible video.

The products on offer are an information good, with utility often declining in repeated viewings. Collins et al. (2009) find that films which are likely to be watched more, specifically children's films, are less likely to be rented due to the value of repeated viewings for children, whereas that value diminishes quickly with adults. Rao (Forthcoming) employs a repeat-consumption utility experiment and observes the declining utility of multiple movie viewings. For this reason, although the titles are accessible as many times as the consumer would like to view them, the vast majority of utility to consumers is likely derived from the first viewing.

Data for this project was collected contemporaneously as no set of historical lineups exists outside of the Netflix organization. By pulling data from the VOD library listings, I collected two years of the evolving offerings available for streaming. The data was collected weekly. The listing data is matched to critical measures of the commercial life of a film prior to its consideration for Netflix. These controls allow for a detailed approach to the decision making used for the products to be bundled.

This paper is unique in content, but there is considerable research into video rentals and sales. Mortimer (2008) studies the contract decisions of video rental stores. Ho et al. (2012) model a similar idea when they use the physical video rental industry from 1998-2002 to analyze bundling consequences among rental stores with consumer and firm data. Zentner et al. (2013) look at how video purchases migrate from physical purchases to online, exploring a possible increase in niche purchases. I use a model of bilateral negotiation to explain the mutual licensing decision of the video.

In this paper I examine the measures of a film important to the VOD library decisions of Netflix, in order to answer the question of what makes mixed bundling profitable among information goods. By using a unique dataset I am able to demonstrate descriptive evidence that among Netflix offerings new products are more profitable to bundle, but are offered for shorter lengths of time due to the need for greater compensation for displacement. Without subscriber data, this is not the only possible explanation, just the most likely. The most and least commercially successful products are not bundled as frequently, but the average product is used more often for bundling. In order to bundle strategically the programmers must make decisions on film choices based not only on the film being considered, but also like films in the library.

2 Background

Recent empirical work on bundling takes advantage of increased data availability of full product lines. Elberse (2010) measures the implications of digital distribution on the unbundling of songs. Crawford and Yurukoglu (2012) consider the implications of bundling television provision. Derdenger and Kumar (2013) observe the complementary nature of the more durable video game console market with bundled information good, the video game title. Danaher et al. (2014b) consider bundling and pricing strategies of song and album distribution in the music industry. The work of Ho et al. (2012) is closest in subject matter to this paper. They use an extensive dataset on rental stores to measure the effect of optimal bundling decisions. While their paper focuses on the contract decision of many rental stores across the country, this paper focuses on a single firm with tremendous market power.

Bakos and Brynjolfsson (1999) consider bundling using information goods in the context of a multiproduct monopolist, and Geng et al. (2005) consider optimal bundling of information goods when the consumer values for the goods declines. While Netflix is not a pure monopolist, the company controlled a significant market share of both DVD rentals and unlimited subscription VOD during this time period in the United States. DVD rentals declined throughout this period, but traditional video rental stores like Blockbuster were driven into bankruptcy, leaving Netflix with millions of subscribers to the physical service.[7] Challenges by companies like Walmart to the DVD rental business had also been overcome well before the beginning of the sample period.[8] Competitors have risen to imitate the subscription VOD service. Hulu.com and Amazon.com offer similar services, but combined account for less than 10% of the VOD traffic of Netflix.[9] Netflix, while not a monopolist, can exercise considerable market power.

Netflix offered more variety in physical discs through the mail than was available on the streaming library during this period. The discs are a pure component offering, and the streaming library a bundle. The physical offering is a subscription rental service. This service is not a bundle, as titles are chosen in advance, and the number of discs available for viewing during any period is limited by the reality of shipping. Discs are available to consumers "in about one business day following our shipment." Allowing

[7]http://www.bloomberg.com/news/2013-11-06/blockbuster-video-rental-chain-will-shut-remaining. Accessed: 12/12/2014.

[8]http://www.nytimes.com/2005/05/19/business/media/19cnd-movie.html. Accessed: 12/12/2014.

[9]http://www.pcmag.com/article2/0,2817,2456230,00.asp. Accessed: 03/11/2015.

for another day for return shipping, and considering the United States Postal Service does not deliver on Sundays or holidays, "a large majority of members rent between 2-11 DVDs per month."[10]

Netflix provides a subscription DVD rental service with tremendous variety, where a small number of those titles are available to consumers at any time. The parallel VOD option of those titles also chosen for the streaming library creates a mixed bundle. The streaming service is widely seen as the future of business for Netflix.[11] These services are in some ways substitutes, although the DVD library has more choice. In contrast to the DVD service, the entire VOD library is available for consumption by subscribers at any time. Strategic choice of movies for the instant library then are made considering the choices could potentially cause consumers to substitute the streaming service for the physical option.

An empirical examination into bundling information goods appears to be new to the literature, but using an experimental setting Koukova et al. (2008) find some evidence that mixed bundling of information goods can be profitable. The logic behind most titles being excluded from the mixed bundle depends on the assumption that inclusion of a title in the VOD library has a displacement effect on sales, necessitating a higher licensing fee. The displacement effect of illegal distribution of digital items has been studied extensively in music (Liebowitz, 2004; Zentner, 2006; Rob and Waldfogel, 2006; Oberholzer-Gee and Strumpf, 2007) and in the film industry (Danaher and Smith, 2014; Danaher et al., 2014a). But as is the case with Netflix, legal avenues of distribution are increasingly displacing more traditional methods. Using a survey of students, Waldfogel (2009) finds some displacement of television with internet content, but an overall increase in viewing. Danaher et al. (2010) exploit the removal of NBC content from iTunes as a natural shock to legitimate content. Hiller (2014) examines a similar removal of Warner music content from YouTube to estimate the impact of streaming music on traditional album sales.

The rights holders of these films face a similar potential displacement from any rental agreement. The reality that only one consumer at a time may use the disc compensates for a possible displacement of sales as the disc is rented to many consumers over time. Netflix makes the choice to buy most releases, but the number of copies of the disc is limited based on current and future expected demand. The VOD service negotiates a licensing fee prior to inclusion in the library, not based on viewing data. This differs from the streaming music market where payouts for songs are dependent on the percent

[10] Quotes from DVD Terms and Conditions, available at https://www.netflix.com/DVDTerms?locale=en-US. Accessed: 12/12/2014.

[11] Many articles speculate on this, and Netflix executives acknowledge its importance. For examples see: http://www.bloomberg.com/bw/articles/2013-10-21/netflix and http://www.wired.com/2011/07/netflix-fees-increase-dvd/

of total plays a single receives, but still depends on total revenue. The reason for this difference seems likely to be related to the difference in consumption habits in music and movies. Where a song is often played repeatedly, a movie is more likely to be watched a very limited number of times. A single viewing of a movie can displace sales leaving the license holder eager to secure the fee before the movie is in the library, a single listen to a song could encourage its purchase. Additionally, given that larger movies have already been in theaters, demand should be easier to predict than demand for new music.

The potential displacement effect for a movie licensed for VOD is much higher. All streaming customers can access the title simultaneously. The licensing fee must be much greater to compensate for the increased potential for lost sales. The decision on which movies will be licensed for streaming then becomes one comparing the marginal utility for consumers of the title to the licensing fee needed to offer it. This model of attracting new and maintaining existing customers through an ever changing library of offerings is similar in idea to (Hiller, Forthcoming). The reality of these decisions shows that the utility of many titles does not exceed the cost, and that the mixed bundle of a single offering and pooled VOD is only suitable for releases which will not experience the displacement of a blockbuster.

Price-per-unit is not a consideration in either the pure component or VOD offerings, as it does not vary across offerings. One limitation of this paper is a lack of data on rental and viewing usage by consumers. The programmers that create the library know the usage data of both offerings, but that data is not publically available. This obvious flaw is overcome by the observation of the entrance and disappearance of titles. An important assumption made for empirical analysis in this paper is that titles will remain in the VOD library as long as consumers derive enough utility from viewing them to purchase a subscription if new, or maintain their subscription if an existing customer. Titles are then removed when it is determined that the licensing fee exceeds the benefit to new and existing customers.

3 Empirical Model Specification

Through the DVD-by-mail service, Netflix offers most if not all of the significant titles released to the public, but only a small portion of those options are also bundled in the streaming service. The sample used in this analysis employs movies available to stream on Netflix as well as recognized major films not in the VOD library, as a full sample of significant movie releases. It is important to emphasize that this is not a decision by Netflix to simply include a film in the streaming library or not offer it at all, all films are available in the physical offering. Rather, the decision is whether to also add a film to the bundle or only offer the physical option.

The choice decision involves the expected profit to Netflix from licensing a film for the VOD library, both through new and continued subscribers deriving utility from the inclusion of the film. Selection into the library and the length of the run of the title are likely jointly made decisions. The programmers decide to license a title, and simultaneously negotiate how long the title will remain in the library, with possible changes in length as the run proceeds. This length decision is known by Netflix and the rights holder, but unknown to the researcher, only the entry and exit decisions are observed. In the analysis that follows, the run is assumed exogenous to the choice decision. The length of the run is analyzed further in the next section.

In order for a title to be licensed to the library, both Netflix and the rights holder must benefit. Conditional on the run, the unobserved profit decision for Netflix is dependent on the characteristics of the film, such as its initial popularity, measured by:

$$\begin{aligned} \pi^*_{ni} = &Revenue^*_{ni}(Popularity_i; Year_i; Studio_i; Genre_i) - \\ &Fee^*_{in}(Popularity_i; Year_i; Studio_i; Genre_i) + \epsilon_n \end{aligned} \tag{1}$$

Where selection of title i for Netflix, n, provides an expected revenue from consumer utility dependent on the box office popularity, age, studio, and genre of the film.[12] As in any bundling decision, when calculating expected revenue the programmers must consider the potential that consumers will substitute the VOD service for the physical service. If consumers simply substitute the streaming option for the physical one, change in revenue from that decision may be neutral. Considering this, I make no assumption that inclusion will bring positive revenue in every case, but that net revenue from the decision overall will be positive. Netflix then has to pay a fee depending on those same characteristics to the rights holder. The marginal cost of providing the film is assumed to be constant and inconsequential to the choice decision. Additionally, the unobserved profit decision of the distributor must be modeled. To agree to license the title and forego some revenue from other distribution channels the rights holder must consider:

$$\begin{aligned} \pi^*_{in} = &Fee^*_{in}(Popularity_i; Year_i; Studio_i; Genre_i) - \\ &OppCost^*_{in}(Popularity_i; Year_i; Studio_i; Genre_i) + \epsilon_i \end{aligned} \tag{2}$$

The profit of licensing title i to Netflix n depends on the same characteristics, but with an opportunity cost associated with the displacement effect of the title being licensed

[12] Bargaining costs are excluded from this paper. If bargaining costs were significant in typical negotiations few low popularity films would be included in the library. While the paper shows that lower grossing films are less likely to be included, there are more films that never had a theatrical run than did.

to the VOD library. Two conditions must hold, first that profit for all films i chosen by Netflix must exceed expected profit of those $-i$ films not chosen, $\pi_{ni} \geq \pi_{n-i}$. Second, the deal is only profitable for the distributor if the licensing deal from Netflix provides at least as much revenue as is lost from appearing in the VOD library, $\pi_{in} \geq \pi_{i-n}$. In order to gain tractability I make the assumption that the fee paid to the distributor is equal to the outside option for the title, $\pi_{in} = 0$. Equation 2 can now be substituted into equation 1:

$$\pi^*_{ni} = Revenue^*_{ni} - OppCost^*_{in} + \epsilon_n - \epsilon_i \tag{3}$$

This provides the intuitive result that the expected profit of choosing a title depends on expected revenue from the title, and the foregone revenue from the selection. The commercial success and year of the film help determine both the expected revenue and opportunity cost for the title. A film will only be included in the VOD library if that expected revenue exceeds the opportunity cost. The remainder of this section is devoted to determining when that condition holds.

The difference in profit of a title i selected versus any title not bundled $-i$ is now:

$$\begin{aligned}\pi^*_{ni} - \pi^*_{n-i} = &Revenue^*_{ni} - OppCost^*_{in} - Revenue^*_{n-i} + \\ &OppCost^*_{-in} + \epsilon_i - \epsilon_{-i}\end{aligned} \tag{4}$$

The error term for Netflix, ϵ_n, is differenced out. Assuming a type 1 extreme value distribution of the error term for titles I estimate this model with a logit regression. The difference in profit between the chosen film and all others, $\pi^*_{ni} - \pi^*_{n-i} > 0$, is not observed. However, the dependent variable, whether or not a title was selected is one for any film where this inequality holds, and zero otherwise.

A functional form for equation 3 is needed to estimate the determinants of title selection. First, I use the following pooled regression of all films in the sample period to determine characteristics associated with selection

$$Selection_{ij} = \gamma_0 + \beta' x_{ij} + \delta' z_{ij} + \gamma_j + \epsilon_{ij} \tag{5}$$

Where x_{ij} is a vector of characteristics related to when film i was released by studio j, including genre and MPAA rating information. The studio indicator should pick up any increased likelihood of a film being selected due to the rights holder licensing many films at once. The commercial success of the film is captured by vector z_{ij}, containing information on the release and gross data of the film in its initial run. The same specification is also used for estimating the run of the film, where the dependent variable is the length of time the film remains in the library rather than selection, and estimation done with least squares regression. A similar model uses exit of films from the library as the dependent variable, depending on the same characteristics as well as the length of time the film has been in the library. The exit model is estimated with a conditional fixed effects logit examining the probability of exit in a given week, and a pooled logit estimating the probability of exit over the entire sample.

Finally, I employ a model of entry that also incorporates the exiting films in the same week as an explanatory variable. This allows for a measure of strategic bundling, where the lineup is curated carefully to maintain a balance of diverse genres, ratings, and time periods to appeal to differing willingnesses to pay. Revenue from adding a film is dependent on how many similar films are already included in the bundle. The specification, estimated with a panel by week, looks much like the previous specifications

$$Selection_{ijt} = \gamma_0 + \beta' x_{ijt} + \delta' z_{ijt} + \phi' Exits_t + \gamma_j + \gamma_t + \epsilon_{ijt} \tag{6}$$

Where the model is similar to the original specification, but with a vector of total exits and specific exits similar to film i in week t, and weekly fixed effects included. The exit data allows for an analysis of strategic bundling selections.

4 Data

Data on the bundled offerings of Netflix had to be collected contemporaneously as no historical database of the library seems to exist beyond the company. I used the website Instantwatcher.com to scrape the entire listing of movies and television shows on a weekly basis. The title of the offering, year, Motion Picture Association of America (MPAA) rating, status as a movie or television show, and average Netflix consumer rating on a 1 to 5 scale were collected for each listing. Entry and exit were inferred by the appearance or disappearance of a title from the library. Television shows are listed by season and special on Netflix and Instantwatcher.

I used two databases to match characteristics to the recognized movie releases in the library: Box Office Mojo and The Numbers.[13] From these I included information on the studio, genre, a rough budget estimate, gross earnings in theaters, the number of theaters in which the title was released, and opening theater statistics of recognized releases, where possible. Titles released before 1973 were excluded from data analysis due to difficulty

[13]Available at http://boxofficemojo.com and http://the-numbers.com. Last accessed 12/5/2014.

matching any titles. All dollar values in this paper are adjusted for inflation using the CPI. The dataset also excludes Netflix original productions as inclusion of this material was always intended, and remains a given.

The dataset includes 104 weeks of the Netflix VOD library from September 6, 2012 through September 4, 2014. Summary statistics for the Netflix library excluding releases prior to 1973 are available in Table 1. There are 9,042 unique movies in this period with release dates ranging from 1973 through 2014 divided into recognized and unrecognized, and television releases. Recognized releases are classified by the ability to match the movie to the extensive combined database of Box Office Mojo and The Numbers. Unrecognized movie releases are those that could not be matched to these databases. Television releases are not the primary focus of this paper, and are not matched to any external database.

The average run on Netflix, or length of time in the library is about 58 weeks, and varies slightly across the categories of offerings, with recognized releases averaging a slightly longer run. $NetflixRun$ includes listings which are available in the first week, and therefore had likely been on the VOD library prior to data collection. Because of this the entire run cannot be calculated. Titles included in the last weeks of the sample present a similar problem, as the run has not ended. Of the 1,810 recognized titles where the entire run, from entry to exit, can be seen in the sample the average length in the library is 40.7 weeks. This estimate is sure to be biased lower than the true average. Of course, as Netflix continues to operate any sample of Netflix offerings can only estimate the average run of a listing from the data obtained, note the potential for bias, and move on.

The availability of budget data is spotty and very roughly estimated, but of those titles with budget data the estimated mean is $29.3 million. This is sure to be biased upward as budget data is more readily available for those costly movies intended for very wide release. $Netflix\ Rating$ is derived from customer opinion of the movies available. Notably, there is a gap between the average ratings of the recognized and unrecognized releases offered. For the unrecognized releases one potential differentiation between truly small movies and those that saw a relatively substantial distribution effort may be whether the MPAA rated the movie for content. Of the unrecognized releases, 30.8% were rated by the MPAA.

Figure 1a shows the evolution of the entire Netflix library over time, through total titles available each week. Interestingly, the number of total titles decreased substantially over this period, with most of the reduction occurring in the number of movies available. This increased relative importance of television shows, coupled with investment in original television series may indicate a strategic shift toward television offerings for the streaming library.[14]

[14]For discussion of original programming see http://iveybusinessreview.ca/cms/3198. Accessed:

The percentage of recognized releases in Figure 1b is not a cross-sectional graph but a look at the number of these titles released in each year that were available in the library at some point during the sample period. Two things to note about these percentages, first, as the Netflix library is constantly changing the percentage of each year's recognized releases will almost certainly increase over time and a longer sample would reflect that. Second, for the later years, particularly 2014, titles are much less likely to appear on Netflix due to the relatively short amount of time between release and data collection. The data shows that a fairly stable percentage of between 20 and 30% of each year's recognized releases, excluding the year 2014, were included at some point in the library. Because of the shortened time frame, titles from 2014 are excluded from the analysis in Section 5.1.

Figure 2 provides information on the number of titles entering and exiting the Netflix library by week for films. Over the course of the two year sample, exit outpaced entry for the entire library, with more net loss in movies than television. Churn is apparent throughout the sample, with a few large spikes in exit as major contracts expire. The largest such spike occurred in week 41, as contracts with Universal and MGM lapsed, reducing the number of offerings. Netflix representatives responded to questions about this reduction by stating they wanted to become a more focused distributor, and the ebb and flow of programming is natural.[15][16] Interestingly, while net gains were made in some weeks before and after this substantial exit, the total number of titles mostly declined throughout the remainder of the sample period.

5 Results

In the data analysis of this paper I first explore a descriptive model of what characteristics of films are important for selection in Section 5.1. This specification focuses on which films are included. Titles not chosen for the VOD library help to illustrate what characteristics are important for bundling, and also the limitations of the VOD bundle model. In Section 5.2 I use the full panel to include strategic exit of films with like characteristics in the selection decision. In Section 5.3 I examine the composition of the bundle throughout the sample, and how that bundle evolves to meet the dynamic needs of attracting and maintaining consumers. The evolution of the bundle provides insight into not just what characteristics make bundling feasible, but also how the bundle must continually change

12/11/2014.

[15] Contract information and quote found at http://www.theverge.com/2013/4/30/4287902/netflix. Accessed: 12/11/2014.

[16] This was not the first substantial decrease in the Netflix library, in February 2012 a lapse in a contract with Starz brought a substantial reduction, http://www.theverge.com/2012/2/27/2828352/netflix-startz-play-content-pulled. Accessed: 12/11/2014.

in the face of rapidly diminishing marginal utility.

The results here lack user usage data, so individual responses to bundle changes are impossible to determine. Analysis of the bundle as profitably chosen depends on two factors, first that the programmers are always chosing films to enter or exit the library with profit maximization in mind. Second, that during this period the numbers of Netflix subscribers and the corresponding profit increased dramatically. Figure 3 shows the dramatic rise in subscribers and profits for Netflix streaming in this period, and is an anecdotal testament to the success of the streaming bundle.[17]

5.1 Movies Chosen for bundling

The results in Table 2 give coefficients for estimation of different functional forms of equation 5, exploring the determinants of the movies selected for the VOD library. Some observation do not have any movie gross and theater release information and columns 1 and 2 exclude those observations, 3 and 4 assume any missing theater values are equal to zero. All weeks are pooled in this regression and the data treated as a cross-section so the selection is of a film over the entire sample period. Columns 1 and 3 use a continuous year variable where 2 and 4 use decade indicators, with all decades compared to the years 2011 through 2013.[18] In the table the marginal effects of a logit regression are displayed, and the coefficients represent the difference in percentage associated with a unit change of the variable compared to a film with mean characteristics.

The newer the film the more likely is selection but those movies released since the turn of the millennium are less likely to be selected. Interestingly, all of this post millennium effect is derived from the first decade after 2000. Movies since 2010 were most likely among all groups to be included in the library, while movies from the first decade of the 2000s were less likely to be selected than those from the previous 20 years. This would seem to indicate that new products are more often profitable to bundle, but also potentially that information goods beyond recent memory may become profitable to bundle again as a sufficient amount of time passes. The films from the early 2000s likely maintain a higher opportunity cost than those from the more distant past.

Films are more likely to be selected as *Gross* increases, but the higher degree terms suggest this effect tapers off for blockbusters. The higher gross of the film implies a greater displacement effect that must be compensated for, and at some point the expected displacement is so great as to counter the additional benefit of increased demand that comes from having the movie in the library. The probability of selection actually decreases

[17]These figures are from the annual report of Netflix.

[18]For the specifications with a continuous year term, a squared year term was initially included, but proved unimportant.

with increasing revenue if the film was made after 2000, as seen by the interaction term *MillenniumGross*. This suggests that the box office success is important for older films, where the outside options and displacement effect are less. With these older films the marginal utility to Netflix consumers of a former blockbuster may be important.

Additionally, a consumer is most likely to see a film soon after its release. After decades have passed, the consumer may have search costs associated with watching a film again. The consumer does not have the recognition or willingness to pay for the title through traditional methods of distribution, but benefits from the film on the VOD library, where the search costs are reduced. For films released in recent years, however, the outside option associated with commercial success is too large to allow frequent bundling. The target of the VOD library for recent releases is a median revenue film. As the titles age, the greater recognition from the higher grossing films coupled with the exhausted distribution, makes the older high revenue title attractive for bundling.

The coefficient on number of theaters supports the mid-level film hypothesis. The mean number of theaters in which a film is released in the sample is 666 for those films where the number is known, and likely zero for those where the number is not. The maximum number of theaters is 4,468 and as the number of theaters increases by 1,000 above the mean, the probability of inclusion increases. But that effect is entirely negated by the square term of theaters, suggesting that a blockbuster released in thousands of theaters actually becomes less likely to be selected for VOD. The theaters may indicate the breadth of commercial success in the film's theatrical run. Netflix may take advantage of the search costs associated with a film that has not been released in many theaters.

5.2 Strategic bundling evidence

In a more detailed bundling model, I explore the evidence that the programmers strategically replace films within the bundle to take advantage of different willingnesses to pay among consumers with differentiated preferences. The model uses the entire panel to examine the probability of selection of a film not in the library in a given week, and the potential for dependencies on the exits of similar films in the same week. Once a film has been selected it is removed from further consideration. A trend variable is included to account for changing numbers entries over time. The sample is limited to recognized titles as they provide sufficient information to compare the exits of similar films.

This model uses a smaller sample, but better accounts for the potential of selection to depend on films already in the library. Consumers may only want to watch a certain number of films in a certain genre, so films in each genre are potentially substitutes for each other. Additionally, programmers want to minimize the number of higher grossing films with their increased licensing fee. Assuming programmers have a certain number of each of these types of movie to maintain in the library, the number of exits in a type will affect the probability of entry of a film not in the library.

Table 3 provides the coefficients on the marginal changes in probability of selection in a given week for this model. While the coefficients are quite small, they must be compared against the probability of the median film being selected in a given week (0.45%). The specification contains the same explanatory variables proven important in the descriptive model, showing qualitatively similar results. The coefficients on $TotalExits$ and $ExitsSimilarGross$ are insignificant, showing the total number of exits and exits of films within $50 million in gross are unimportant. A reduction in films is not enough to increase the probability of entry, which films exit determine which films enter.

The remaining exit variables are important for the probability of entry for a film. An additional exit of a film with the same MPAA rating ($ExitsSameMPAA$), for example a "PG" rating, is associated with an increase in likelihood of 0.077 percentage points, or about a 17% increase for the median film. The rating system may serve as a proxy for age of viewers, with children more likely drawn to "G" or "PG" films, while adults often focus on "PG-13" or "R" ratings. Keeping the appropriate balance encourages subscribers with children and subscribers without children. Adding films to the library may then depend heavily on the demographics of existing films.

Similar estimates exist for genre. An example here could be films considered to be comedies, where a film classified in this genre is much more likely to be included as other comedies exit, given a declining marginal utility of additional comedies in the library. The Netflix interface introduces subscribers to films by genre, so maintaining a sufficient number of each genre is important. But overrepresentation of a genre will not help to gain or maintain subscribers. Finally, the importance of age of the film shows with a smaller but significant effect for decade. Again, this could be dividing consumers into age brackets, evidence of strategic bundling.

These coefficients indicate the need to strategically bundle. The library likely maintains a careful mix of genre, age, and MPAA rating to take advantage of the potential for strategic bundling. As films are an information good with a utility that is quickly depleted, the bundle churns constantly. But this specification indicates that programmers are not aiming for simply the best film, but rather the best film that is available and maintains the balance of the bundle.

5.3 The evolution of the Netflix VOD library

Commentary examining the VOD library of Netflix is filled with discussion on the obscurity of the available movie titles.[19] Indeed, services have been started to help comb through the Netflix offerings.[20] But as the number of movie titles is reduced over the sample period, it appears the bundling strategy is to choose the remaining titles from more recognizable selections. Figure 4 shows the percentage of movies that could be matched to a database, as well as the percentage of movies released by a major studio by week.[21] The clear trend in each graph is toward a library which is more recognizable and more often released from large studios. Figure 5 supports this interpretation. The average budget and gross of movies in the VOD library rose substantially as the library shrank.[22] Additionally, the average opening of movies increased during this period. While the bundle is decreasing in size, the remaining movie releases are increasingly prominent.

The characteristics that help determine how long a title remains on Netflix are similar to the selection decisions, examined in Table 4. This sample only includes titles for which I could observe the entire Netflix run, or entry and exit within the sample period. Netflix original productions are excluded as they are not subject to exit. Columns 1 and 2 exclude those unrecognized titles without gross or theater data, leaving only recognized titles. Columns 3 and 4 include all observations with a run that is observed in its entirety, with the assumption that missing theater and gross data imply a zero value. All specifications in this table are estimated with least squares regression.

In contrast to the analysis of which movies are chosen, the newer releases in the VOD library experience a shorter run. The decade indicators in columns 2 and 4 show this result is a bit more nuanced. In a complete reversal of the movies chosen, the most recent releases experience the shortest run of any period within the last 35 years. New titles are more likely to be chosen because of immediate demand, but not kept in the library for long. This is likely related to the nature of movies as information goods with rapidly diminishing marginal utility. Newer films are more easily recognized, promoted more, and viewed quickly. Bundling these goods requires considerable churn, and the newest titles necessitate the most churn.

The gross revenue of the film is not a significant determinant of how long titles are in the VOD library. The other box office success measure, number of theaters in which the title played, shows a negative coefficient. This is potentially related to the distribution network that exists for the film. A film which is in many theaters is more likely to already

[19] This commentary is both serious and satirical, as seen by the "fake news" website *The Onion*: http://www.theonion.com/articles/netflix-instant-thinking-about-adding-good-movie Accessed 1/2/2015.

[20] See http://instantwatcher.com and http://whatisonnetflix.com/. Accessed: 12/15/2014.

[21] Major studios are defined as any with at least 15 films or 0.2% of the films in the sample.

[22] Budget numbers are very rough estimates with a small sample, and should be interpreted accordingly.

have an extensive distribution network. Inclusion in the VOD library would involve a greater opportunity cost from this network, so if included the run will be shorter. These two results seem to indicate that while success is important to what movies enter the library, if any relationship exists between success and the run it is negative.

The average rating consumers provide for the title on Netflix helps to determine the run. An increase of one point is correlated with a two week increase in the length over the average title in the full sample, and a nearly six week increase in the recognized titles. The result supports the economic reality that the recognized titles require a higher licensing fee, and the run of these titles must be very closely monitored to match consumer opinion. Existing customers would be more likely to have knowledge, and demand, of recognized titles resulting in lower search costs and quicker consumption than for unrecognized titles. The higher rating by these existing consumers of recognized titles may act as a signal that extending their run may be warranted, despite higher licensing costs, in pursuit of new customers. Alternatively, this could be the programmers of the bundle successfully predicting which films will have a higher rating, and licensing those films for a longer run in the original contract.

The churn statistics in Table 5 give the mean percentage of total, recognized, and unrecognized movies that enter and exit each week. The statistics show that while recognized titles churn less than unrecognized titles on average, recognized titles have a lower variance of entry and exit. Additionally, exit outpaced entry throughout the period. This difference was substantial in unrecognized titles but small among recognized titles. The number of recognized titles in the library in a given week must be more tightly regulated and less subject to fluctuation than unrecognized titles.

Table 6 provides a descriptive specification using a panel analysis of the likelihood of exit for titles in each week in columns 1 and 2 of all films already in the library, and a pooled regression comparing characteristics of films that exit to those that do not in columns 3 and 4. Columns 1 and 3 drop any observation where gross or theater data is missing, and 2 and 4 assume those values are zero. The length of time a title has been in the VOD library, $CurrentRun$, as well as its square term are new in 1 and 2 as the dataset is now treated as a panel by week over the entire two year sample, as well as a variable $PreSample$ that is included if the film enters before the sample period.

The results show that the probability of exit increases in the panel with each week that passes for a title, as would be expected mechanically. More recent films are less likely to exit in any given week, but that effect is countered for films released after the year 2000. Interestingly, gross revenue is not significantly correlated with exit, consistent with results in the regression measuring the run, but the number of theaters is important. One explanation is that the number of theaters is strongly correlated with a robust distribution network and superior outside options. Columns 3 and 4 pool the characteristics of films to compare the likelihood of exiting during the sample period. This model allows for the inclusion of data where exit cannot be observed, by dropping those added before the sample begins and comparing an exit decision to all films where the entrance can be observed. A fixed effect for entry week is included to compare between peer films. Results are qualitatively similar to the panel regression. The larger coefficients are logical given the substantially increased likelihood of exit of the median film in the entire sample period over the likelihood of exit in a week of the panel regression.

6 Conclusion

Bundling a film requires an expected revenue from additional consumer utility that exceeds the foregone revenue that comes from the bundling. In order to make the practice profitable, a streaming service like Netflix must take into account the age of release, commercial success, and distribution network of the title as well as films already in the library. The observed actions of Netflix indicate that an information good may be profitably bundled most often when sufficient time has passed to see the substantial opportunity costs of displacement diminish for successful titles, and with bundling soon after release for titles that were not commercially successful or widely distributed. The bundling is strategic, as entrance depends not simply on the characteristics of the film, but also the numbers of similar films exiting in the same period.

There are two distinct limitations to bundling titles, compensation for the displacement effect of inclusion in the VOD library for successful films and a lack of demand for all others. Among recognized releases, the film with middling success is most likely to be bundled, as the sales displacement can be compensated for. The high grossing information good is rarely profitably bundled until well after its release. For goods with lesser commercial success, and for unrecognized titles, the lack of demand for the product makes bundling unprofitable. The titles in this category that are included in the VOD library are identified as quality films that did not have the distribution to create considerable demand outside of the bundle. The bundle is likely serving to reduce search costs for these products, therefore adding value.

Netflix programmers provide evidence of strategic bundling. The balance among differentiated preferences must be maintained, as the desired mix of film characteristics must appeal to the differing willingnesses to pay based on genre, age, and MPAA rating. A bundle of information goods must churn continuously, as the value of the information is consumed. Observing the evolution of the library through the length of the run and churn of titles indicates that once the decision has been made to include the film in the library, distinct factors determine how long it will stay there. Specifically, how much subscribers enjoy a title once they find it is important, as well as how long ago it was released. Information goods that are not recent, but still highly rated, are particularly likely to have a long run. This can be explained by a lower opportunity cost from the displacement effect while still maintaining a significant utility for consumers.

These results have general implications for information goods, but also many specific implications for streaming video and bundled internet delivery services. First, highly successful films are unlikely to be available for bundling because of the opportunity cost. While rental companies such as Blockbuster have failed, this has opened the door for smaller retail outlets such as Redbox and digital distribution of rental films by giants like Amazon. Some combination of a bundled streaming service for older and median success titles with a smaller outlet for higher grossing recent films likely benefits consumers.

Finally, internet delivery is changing how information goods are consumed. In response to the bundled library of Netflix, competitors Amazon and Hulu have entered the fray with bundled VOD. Future work could focus on the competitive response to these challenges. This paper neglects the consumer utility side of bundled information goods out of necessity. No data on the viewing habits of consumers was available. These statistics would enhance the level of analysis. While the assumption is that consumers receive an improved experience, any effects could be quantified with detailed data.

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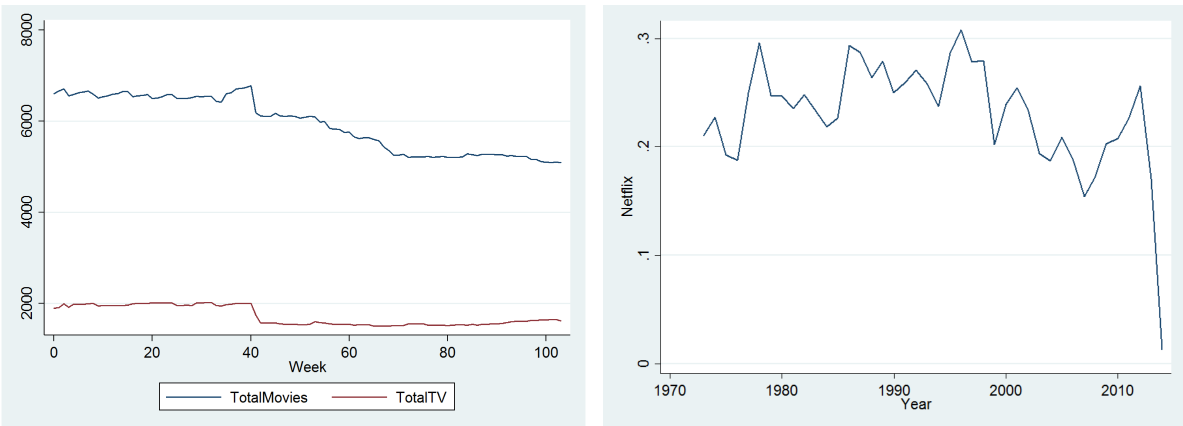


(a) Totals over time

(b) % of recognized releases selected

Figure 1: Netflix summary statistics

Table 1: Summary statistics for Netflix titles

Variable	Mean	Std. Dev.	Min.	Max.	N
Recognized movie releases					
Netflix Run	58.86	34.24	0	103	3849
Netflix Rating	3.33	0.41	1.5	4.5	3849
Year	2002.6	8.69	1975	2013	3849
Theaters	0.67	0.98	0.001	4.39	3849
Gross	10.05	23.17	0	374.32	3849
Budget	29.32	32.52	0.001	200	1041
Opening	3.43	8.36	0	152.53	3744
Unrecognized movie releases					
Netflix Run	57.68	32.39	0	103	5193
Netflix Rating	3.09	0.55	1.4	4.7	5193
Year	2002.9	9.91	1973	2013	5193
MPAA Rated	0.308	0.14	0	1	5193

Notes: Netflix Run is in weeks. Gross, Budget, and Opening are in millions of dollars. Budget should be considered a rough estimate.

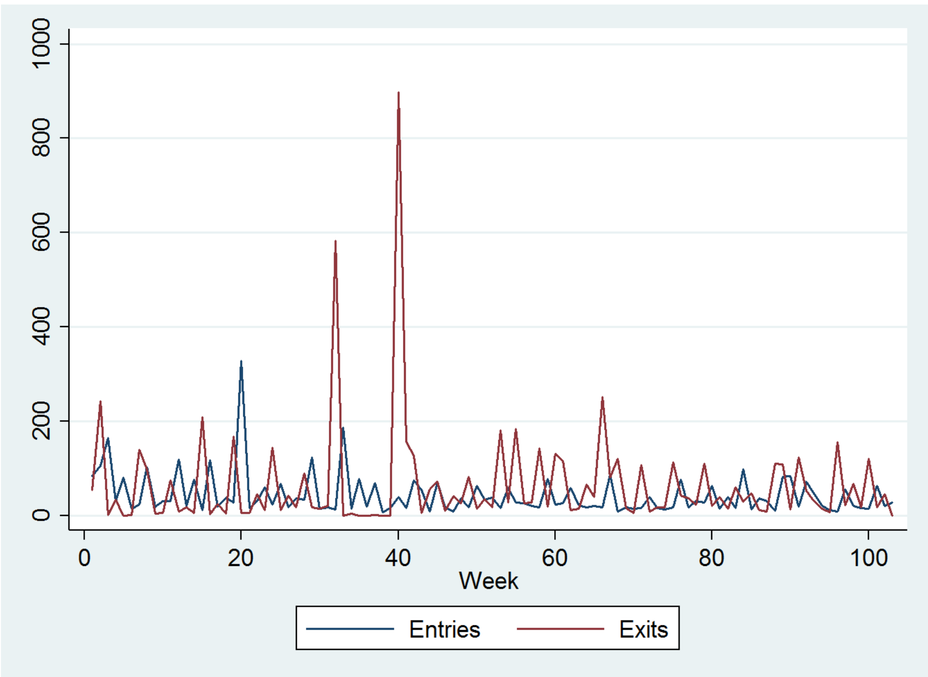


Figure 2: Movie entry and exit

Table 2: Movies chosen by Netflix

	(1) Cont. Year	(2) Decade	(3) Cont. Year	(4) Decade
Year	0.0057***		-0.00097	
	(0.0013)		(0.00080)	
Millenium	-0.10***		-0.027*	
	(0.023)		(0.016)	
MilleniumGross	-0.0024***	-0.0023***	-0.0020***	-0.0019***
	(0.00057)	(0.00057)	(0.00040)	(0.00040)
Gross	0.0060***	0.0061***	0.0031***	0.0033***
	(0.00078)	(0.00077)	(0.00043)	(0.00044)
GrossSq	-3.6e-05***	-3.6e-05***	-1.6e-05***	-1.7e-05***
	(6.8e-06)	(6.8e-06)	(3.1e-06)	(3.2e-06)
GrossThird	5.0e-08***	5.0e-08***	1.6e-08***	1.7e-08***
	(1.3e-08)	(1.3e-08)	(4.1e-09)	(4.0e-09)
Theaters	0.011	0.012	0.089***	0.086***
	(0.022)	(0.022)	(0.015)	(0.015)
TheatersSq	-0.013*	-0.015**	-0.020***	-0.022***
	(0.0071)	(0.0070)	(0.0049)	(0.0050)
MinorStudio	-0.10**	-0.094**	-0.21***	-0.21***
	(0.047)	(0.047)	(0.033)	(0.033)
Seventies		-0.16*		0.028
		(0.089)		(0.029)
Eighties		-0.12***		0.014
		(0.026)		(0.016)
Nineties		-0.034		0.038***
		(0.021)		(0.013)
Aughts		-0.11***		-0.013
		(0.014)		(0.0091)
Median Film Pr.	0.367	0.367	0.244	0.244
N	7798	7798	12991	12991

Standard errors in parentheses. Gross is in millions of dollars, theaters in thousands. Estimation is done with a Logit regression depending on selection in the Netflix library. Genre, studio, and MPAA indicators are included in the regression, but excluded for space. All coefficients represent the marginal difference in probability compared to the median film.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Panel of movies chosen with exits

	(1) Cont. Year	(2) Decade
Year	9.2e-05***	
	(0.000016)	
Millenium	-0.0012***	-0.0042**
	(0.00027)	(0.0020)
MilleniumGross	-3.6e-05***	-3.8e-05***
	(7.7e-06)	(7.8e-06)
Gross	6.1e-05***	5.3e-05***
	(1.0e-05)	(1.0e-05)
GrossSq	-3.2e-07***	-2.8e-07***
	(9.0e-08)	(9.0e-08)
GrossThird	4.0e-10**	3.3e-10*
	(1.7e-10)	(1.8e-10)
Theaters	0.00029	0.00027
	(0.00025)	(0.00025)
TheatersSq	-0.00021**	-0.00017*
	(9.1e-05)	(9.0e-05)
TotalExits	-1.5e-09	-1.5e-09
	(9.8e-10)	(9.9e-10)
ExitsSimilarGross	0.00026	0.00027
	(2.8e-04)	(2.8e-04)
ExitsSameMPAA	0.00077***	0.00077***
	(1.8e-05)	(1.8e-05)
ExitsSameGenre	0.00082***	0.00085***
	(5.4e-05)	(5.4e-05)
ExitsSameDecade	0.00015***	0.00013***
	(1.8e-05)	(1.8e-05)
Seventies		-0.0070***
		(0.0023)
Eighties		-0.0057***
		(0.0020)
Nineties		-0.0056***
		(0.0020)
Aughts		-0.0019***
		(0.00017)
Median Film Pr.	0.0045	0.0045
N	850059	850059

Standard errors in parentheses. Gross is in millions of dollars, theaters in thousands, exits in hundreds. Coefficients represent the difference in probability compared to the median film. Fixed effects are included in the regression, but excluded for space.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Length of run on Netflix

	(1) Cont. Year	(2) Decade	(3) Cont. Year	(4) Decade
Year	-0.42***		-0.69***	
	(0.16)		(0.10)	
Millenium	11.9***		13.7***	
	(3.10)		(2.36)	
Rating	5.83***	5.80***	2.00**	2.35**
	(1.84)	(1.86)	(1.00)	(1.00)
MinorStudio	-5.75	-5.51	5.58	4.75
	(7.22)	(7.24)	(7.43)	(7.41)
MilleniumGross	-0.071	-0.065	-0.078	-0.052
	(0.078)	(0.078)	(0.079)	(0.079)
Gross	-0.019	0.049	-0.074	0.0021
	(0.079)	(0.079)	(0.076)	(0.076)
GrossSq	0.00013	-0.00013	0.00040	0.00013
	(0.00046)	(0.00046)	(0.00047)	(0.00047)
Theaters	-4.98*	-6.88**	-5.86**	-10.8***
	(2.80)	(2.94)	(2.80)	(2.87)
TheatersSq	0.77	0.94	1.37	2.27**
	(0.99)	(1.02)	(1.00)	(1.02)
Seventies		-8.09		-1.84
		(5.23)		(2.81)
Eighties		-2.94		5.35**
		(3.15)		(2.21)
Nineties		-4.35*		4.89***
		(2.63)		(1.79)
Aughts		3.16		9.81***
		(2.13)		(1.20)
Constant	53.3***	24.2**	72.5***	15.6
	(16.3)	(10.8)	(23.4)	(22.0)
N	1810	1810	4176	4176

Standard errors in parentheses. Gross is in millions of dollars, theaters in thousands. Columns 1 and 2 assume values of zero for observations without gross or theater data. Columns 3 and 4 exclude those observations. Genre, studio, and MPAA indicator variables are included in the regression, but excluded for space.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Average movie churn in a week

Variable	Mean	Std. Dev.	Min.	Max.
Total Exit	0.01	0.015	0	0.116
Total Entry	0.006	0.006	0	0.043
Recognized Exit	0.009	0.013	0	0.071
Recognized Entry	0.008	0.008	0	0.042
Unrecognized Exit	0.01	0.018	0	0.145
Unrecognized entry	0.006	0.006	0	0.043
N		104		

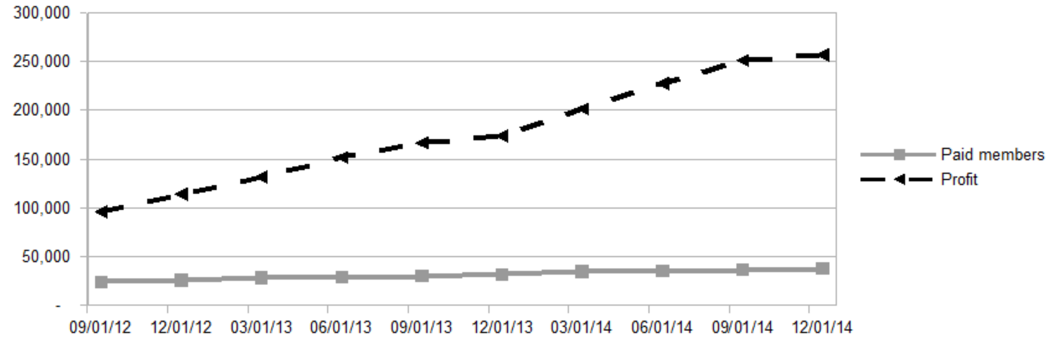
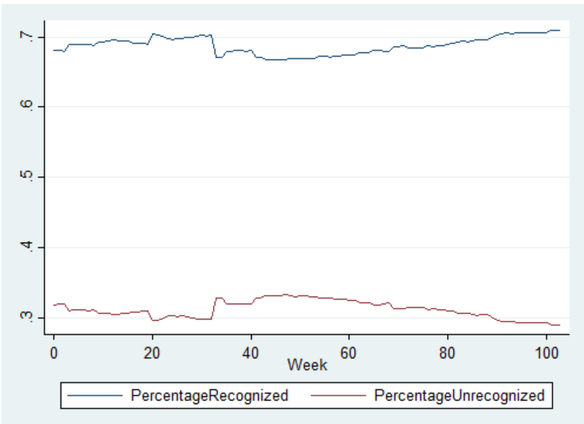
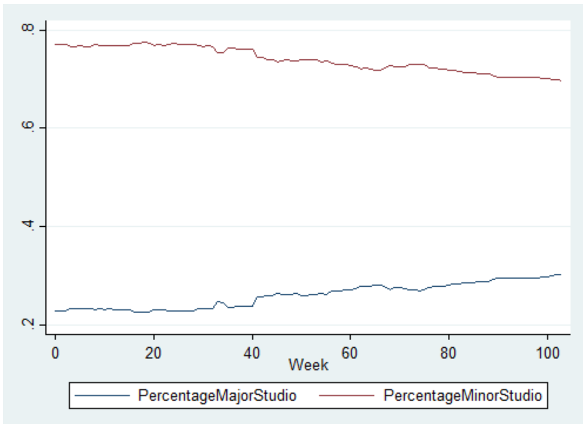


Figure 3: United States subscribers and profits (in 1000s)



(a) % of movies recognized



(b) % of movies from major studios

Figure 4: Movie library prominence

Table 6: Probability of exit

	(1)	(2)	(3)	(4)
	Panel	Panel	Pooled	Pooled
PreSample	0.0028***	0.0080***		
	(0.00064)	(0.00061)		
CurrentRun	0.00033***	0.00034***		
	(3.7e-05)	(3.2e-05)		
CurrentRunSq	-1.82e-06***	-1.8e-06***		
	(2.9e-07)	(1.9e-07)		
Year	-0.00052***	-0.00034***	-0.016***	-0.0076***
	(7.6e-05)	(4.1e-05)	(0.0028)	(0.0014)
Millenium	0.0033***	0.0041***	0.020	-0.031
	(0.0011)	(0.00072)	(0.047)	(0.031)
Rating	-0.0040***	-0.0021***	-0.097***	-0.025*
	(0.00078)	(0.00038)	(0.033)	(0.015)
Gross	-2.6e-05	-4.2e-05	-0.0020	-0.0021
	(3.5e-05)	(3.3e-05)	(0.0014)	(0.0010)
GrossSq	-1.7e-07	-4.4e-07	4.4e-06	-1.8e-07
	(2.1e-07)	(2.9e-07)	(7.8e-76)	(6.0e-06)
Theaters	3.6e-06***	6.6e-06***	5.6e-05	0.00011***
	(1.2e-06)	(1.1e-06)	(4.7e-05)	(3.6e-05)
TheatersSq	-3.2e-10	-1.5e-09**	4.6e-09	-1.9e-08
	(3.8e-10)	(3.6e-10)	(1.5e-08)	(1.2e-08)
MinorStudio	-0.0082***	-0.0090***	-0.27***	-0.24***
	(0.0013)	(0.0013)	(0.064)	(0.055)
Median Pr. Exit	0.0085	0.0094	0.374	0.306
N	215129	614641	1258	3400

Standard errors in parentheses, clustered by studio. Coefficients represent the marginal difference in probability of exit associated with a one unit change in the dependent variable. Studio, genre, and MPAA indicators are included in the columns 1 and 2, additional week of entry indicators in 3 and 4
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

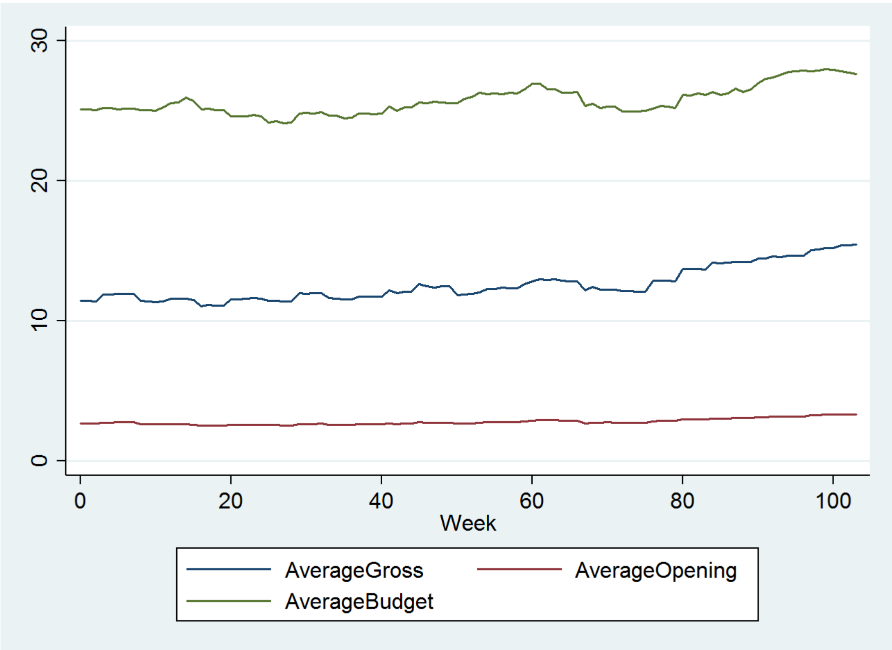


Figure 5: VOD library statistics (in millions)