IS TOM CRUISE THREATENED?

AN EMPIRICAL STUDY OF THE IMPACT OF PRODUCT VARIETY ON DEMAND CONCENTRATION

Completed Research Paper

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Abstract

Multiple studies suggested that expanding product variety due to adoption of the Internet will satisfy consumer's increasingly heterogeneous tastes, thus causing the so-called Long Tail effect (i.e., increasing demand for niche products). In this paper we empirically examine the impact of product variety on demand concentration. We use two large data sets from the movie rental industry and analyze the data at both movie-level and consumer-level. We employ multiple measures to understand the changing demand concentration and incorporate the potential endogeneity of product variety. Multiple models analyzed in our study consistently suggest that larger product variety is likely to increase the demand for hits and decrease the demand for niche products. We propose that new products appear much faster than consumers discover them. Finally, we find no evidence that niche titles satisfy consumer tastes any better than popular titles and that a small number of heavy users are more likely to venture into niches than light users.

Keywords: Product variety; demand concentration; A-B-C classification; movie rental; the Long Tail effect; product rating; customer satisfaction; e-commerce; search cost; online behavior

Introduction and Related Literature

Chris Anderson, editor-in-chief of *Wired Magazine*, coined the term “Long Tail effect” (Anderson, 2004) suggesting that, due to the introduction of the Internet, niche products will comprise higher and higher market share, while the demand for hit products will continue to decrease. As a result, he predicted that the old Pareto rule, stating that 20% of all the products generate 80% of the revenues, will no longer hold: hit movies will constitute a smaller and smaller proportion of demand. His predictions of the Long Tail effect were motivated by observations in the media, entertainment and other industries. For example, Anderson (2006) finds that the top 50 best-selling albums of all time were produced in the 70s and 80s; none of them were recorded in recent years. He also observes that the ratings of the top TV shows have gradually decreased and that the top show today would not have ranked among the top ten in 1970. Part of the reason, according to Anderson, is that niche products will better and better satisfy consumer preferences because consumers will continue to have more and more varying preferences while the Internet will make even the most obscure products available to the masses.

The potential for the existence of the Long Tail effect is of great importance for product assortment decisions in a variety of industries, for advertising dollars spent on supporting this variety, and for supply chain management of these products on the Internet. For example, Blockbuster stocks 3,000 DVDs per store on average, while 20% of Netflix rental revenues come from outside the top 3,000 titles (Anderson, 2004). In addition, Ecast, a digital jukebox company, sold 98% of its 10,000 albums available online at least one track per album per quarter (Anderson, 2006), while brick-and-mortar music stores only stock a fraction of this variety. If demand is indeed shifting toward more obscure titles, managers should ensure that these titles are available and that they are advertised properly. Further, Anderson explains that the new online recommendation systems help the niche products quickly find their demand in the market once they are made available. As a result, he asserts that “the tail of available variety is far longer than we expected”, and that the combined market share of the niches can outgrow the hits (Anderson, 2006). This comment about the increasing demand for the niches seems to be consistent with Varian’s opinion in light of the cheaper technology in the media industry. Specifically, Varian (2006) notes that this “creative, inexpensive and compelling semiprofessional content available via the Internet” has an increased demand particularly among young people, so that the salaries of celebrities, such as Tom Cruise, may decrease. He explains, “It is true that there is only one Tom Cruise, but it is equally true that there are only 24 hours in a day. The more time young people spend watching Lonelygirl15, the less time they will have to watch Mr. Cruise.”

Is popular celebrity Tom Cruise really threatened by Lonelygirl15? Although arguments and evidence in favor of the Long Tail effect appeared pervasive at first, there are also indications that hits still drive some markets, and may even become more popular over time, whereas the rising demand for niches is, at best, overestimated. In particular, some evidence suggests that new products appear so quickly that consumers have no time to discover them. Gomes (2006) discloses that at Ecast, the quarterly no-play rate increased from 2% to 12% as product variety has grown. In addition, an even stronger demand for hits is found in the motion picture industry, where both the number of movies that generate box-office revenues of over $50 million and their percentage of the total revenues increased from 14 and 14% in 1998 to 19 and 22% in 2003, respectively (Eliashberg et al., 2006). Finally, Orlowski (2008) reports on an industry study which discovered that 80% of the digital song inventory sold no copies at all - and the ‘head’ of the frequency distribution was far more concentrated than expected. Given this conflicting evidence, whether or not the Long Tail effect exists remains a hotly debated issue among practitioners.

The Long Tail effect has also recently generated widespread interest in academic circles. Brynjolfsson et al. (2006; 2010; 2011) present plausible factors that may drive the Long Tail effect, including both supply-side and the demand-side effects. On the supply side, they suggest that the Internet reduces the production and distribution costs of niche products, creating more products available. These products can satisfy consumer's increasingly heterogeneous needs, thus driving the Long Tail effect. On the demand side, they note that both the active and the passive search and personalization tools lower the search costs and hence facilitate finding niche products. Consistent with this view, Cachon et al. (2008) find that the lowered search costs have market-expansion effect, which encourages firms to enlarge their assortment. As a result, consumers are more likely to find niche products, thus causing demand for them to increase. Moreover, Tucker and Zhang (2009) suggest that product popularity information, such as the number of people who have browsed the product, can increase the appeal of niche products disproportionately. In addition, Kumar et al. (2011) find that broadcasting movies on pay-TV can increase the the awareness of unpopular movies, thus reducing the demand concentration of DVD sales.

However, several studies have shown opposite results of the Long Tail effect. Ghose and Gu (2006) argue that search costs are even lower for popular products than for niches, which may limit the Long Tail effect. Hervas-Drane (2009) provides an analytical model to show that different search processes have mixed impacts on demand concentration. Moreover, Fleder and Hosanagar (2009) suggest that sales diversity can be reduced by selection-biased recommendation systems because these systems tend to recommend products with sufficient historical data (i.e., hits). From a field experiment, Fleder et al. (2009) further find that consumers buy a more similar mix of music after receiving recommendations than before. Dellarocas and Narayan (2007) also find that online consumers are more likely to review popular products, and therefore, online reviews may exhibit "tall heads" instead of "long tails". Bockstedt and Goh (2008) analyze the data of consumer-created custom CDs to examine whether people tend to bundle the hits or the "long tail" music and suggest that managers should sell unbundled information goods to meet the demand from the mainstream consumer. Elberse and Oberholzer-Gee (2008) find further evidence that online retailing triggers demand to shift toward the tail of the distribution, although they also find that a substantive part of demand is concentrated on an even smaller portion of products.

So far, both academic theories and the empirical evidence provide what can probably be described as conflicting evidence for the existence and the magnitude of the increased demand for niche products: while there are many anecdotal examples of its presence, there are fewer than a handful of rigorous and large empirical studies both at the product and consumer levels. Furthermore, previous research has implicitly assumed that expanding product variety will satisfy consumer's increasingly heterogeneous tastes, which causes the Long Tail (e.g., Brynjolfsson et al. 2006; Brynjolfsson et al. 2010). Little research has empirically confirmed the impact of product variety on the demand concentration. For example, Brynjolfsson et al. (2011) controlled for the differences of product availability between online and offline channels, which excludes the impact of product variety. Tracking weekly video sales from 2000 to 2005, Elberse and Oberholzer-Gee (2008) define hits as the top percentiles of all the movies across the entire six years. In other words, they create a static definition of hits for all the movies over a span of six years, which implicitly excludes the impact of dynamic product variety. In a relevant study, Hinz et al. (2011) use aggregate video-on-demand data in Germany and study the effect of product variety on the share of purchased products. Nevertheless, this study does not examine the demand concentration impact, which is typically a debate focus on the Long Tail effect.

Although little research has been done to explicitly examine the impact of product variety on the demand concentration, whether or not the demand for niche products increases amid an ever-changing product variety is a fundamental question for decision-makers in operations, marketing and finance, particularly when they face the prospect of further penetration of the Internet channel, which offers expanding product variety and new recommendation systems to help manage it.

In this paper we empirically evaluate the impact of product variety on the demand concentration. We use two large data sets from the movie rental industry and report results at both movie-level and consumer-level. The first data set contains rental activity of about 30% of the entire U.S. market from January 2001 to July 2005. The other data includes 100 million online ratings of 17,770 movie titles by 480,000 users on Netflix during the same period of time. The movie rental industry, particularly Netflix, is a key example in Anderson's evidence for the Long Tail effect and he primarily refers to the popularity of products in absolute terms, e.g., the top 100 or the top 1000 for hits. In his own words, "number one is still number one, but the sales that go with that are not what they once were" (Anderson, 2006). Following this example, we first measure movie popularity in absolute terms and find counter-evidence that demand for hits actually increased.

The above definition of the Long Tail effect and movie popularity is static, which implicitly excludes the impact of an increasing product variety. This definition would certainly reflect product popularity in a channel where product variety is relatively stable and where all products are consumed, such as in a brick-and-mortar store. However, product variety has skyrocketed during the Internet age, and more products than ever are not being discovered by consumers (Brynjolfsson et al., 2003). Such a dramatic increase in product variety is likely to create demand diversification. For example, given a choice set of only five movies, people may tend to concentrate their demand on one movie whose popularity rank is number 1 or equivalently in the top 20%. However, out of a wider choice set of 500 movies, the demand may be concentrated on 100 movies whose popularity ranks in the top 100 or also in the top 20%. This example causes a conflicting definition of hits and niches amid different sizes of product variety at different points in time. Should we classify the top 20%, which is respectively the top one out of five movies and the top 100 out of 500 movies as the hits, or should we restrict the label of hits to only the top one movie regardless of the total variety?

Naturally, when the product variety is large, the demand for any one product tends to be smaller than when the product variety is small. Likewise, when the consumer base is large, learning about new products is faster than when the consumer base is small. In this case, two competing effects might be observed: 1) consumers discover the obscure products as they appear and 2) new products appear, possibly so quickly that most consumers have no time to discover them. Which effect dominates is an empirical question that we aim to address in this paper. Therefore, we propose a dynamic definition of product popularity which adjusts for active product variety. The active product variety excludes the titles that have no current rentals or ratings and therefore reflects the dynamics of both product variety and consumer base. As one specific case, we use the A-B-C classification, which traditionally groups products into three classes in inventory management literature (Silver et al., 1998). In particular, Class A products, which comprise the most popular 20% of the product variety, usually contribute to 80% or more of the total demand, thus requiring the highest priority of managerial attention. Class B items, which comprise the products that rank between top 20% and top 50% of total products, usually account for the rest of the 20% of the total demand. Class C products, which are the largest class including the remaining products 50% of all products, generally contribute the least to the total demand. Using A-B-C classification not only allows us to account for the dynamic product variety, but also provides insights to the demand for the "mid-tail" products, which are not as easy to identify as the "head" and the "long tail" products (Jiang et al., 2011).

We find that an increase of 1,000 new movies per month in the product variety increased the demand for Class A movies by about 0.97%, whereas it decreased the demand for Class B movies by 1.74% and for Class C movies by 4.8%. These findings suggest that product variety intensifies demand concentration, which is also manifested by changes in monthly Gini coefficients as product variety changes: 1,000 new movies per month may increase demand inequality by 0.13%. In order to address the potential endogeneity of product variety, we use an instrumental variable approach and show consistent results. Similarly, at the consumer level, we find that new products appear so quickly that most consumers have no time to discover them, causing them to watch more and more hits. Furthermore, while Anderson (2004, 2006) argued that more and more consumers will choose niche products because they will tend to satisfy consumer preferences better, we reveal that consumers tend to be less satisfied with niche and less popular movies that with popular ones. We also find that it is mostly the heavy users or the "movie buffs", a small fraction of all consumers, that venture into niche movies.

To summarize, the contributions of this paper are three-folds. First, we examine the implicit assumption about the impact of product variety on demand concentration and provide new counter-evidence against the Long Tail. We show that product variety increases the demand for hits even when popularity is measured in an absolute sense. Second, we propose to delineate two effects: demand diversification due to expanding product variety and consumers learning about new products. We suggest that, when measuring product popularity, one has to use relative measures such as A-B-C classification to adjust for instantaneous active product variety. With this definition, we find that product variety increases demand concentration on hits, which is against the Long Tail prediction. Third, we study demand at the consumer level and find that new movies appear so quickly that most consumers have no time to discover them, and that niche movies do not satisfy consumer tastes better than hit movies.

Hypothesis Development

In this section, we develop our hypotheses about the impact of product variety on demand concentration. In particular, we discuss how expanded product variety limits the assumptions of some conventionally-held drivers that would predict the Long Tail effect.

Previous studies argue that producers and retailers have increasing incentives to produce and stock niche products because of lowered production and inventory costs (e.g., Brynjolfsson et al. 2006l; 2011). This increased product variety is further assumed to better and better satisfy consumer preferences because consumers will continue to have more and more varying preferences, thus leading to the Long Tail effect (e.g., Anderson 2006).

While there is little doubt that product variety generally increases and that technology such as the Internet and drop-shipping techniques allows companies to offer an even wider variety of products economically, it is less clear that consumers necessarily quickly discover these products let alone actually consuming these products. Large product variety is likely to make it more difficult to notice new products. In other words, a change from two to three options in the choice set can be easily noticed, but it takes a lot more effort to notice a change from 2,000 to 2,001 options. New products that have limited associated advertising budgets to create "buzz", particularly those niche products, may disproportionately emerged unnoticed, thus jeopardizing their demand.

In addition, although consumers may have varying tastes and like to seek variety, they are less likely to examine all choices to find their "true" fit of tastes when they are faced with large product variety. Too many choices require more cognitive efforts to evaluate the attractiveness of alternatives in the large variety (see Kuksov and Villas-Boas 2010 for a review), thus increasing search cost. When search cost is high, consumers tend to restrict their choice consideration to the products for which they have ex ante knowledge (Stigler, 1961; Rothschild, 1974). These products tend to be popular products because they are more likely to have louder buzz from advertising, promotion and word-of-mouth. As a result, demand is likely to be even more concentrated on those hits.

Furthermore, good-quality products may seem even more attractive in the large product variety. Simonson and Tversky (1992) suggest that adding extremely lower-quality products into a consideration set can increase the attraction of the higher-quality products. Therefore, introducing more lower-quality products, which tend to be niches, is likely to make higher-quality products, which tend to be hits, even more popular. In addition, when product variety is large, consumers are found to be more discriminating in terms of product quality (Bertini et al., 2011), which can further increase the demand for the hits.

For these reasons, we hypothesize that

HYPOTHESIS: *Product variety is positively associated with demand for hits and negatively associated with demand for niches.*

Data

Research Setting and Data Collection

To examine our research hypothesis, we gathered data available from a company that leases and delivers movies to rental retailers. Its clients represent approximately 30 % of the entire U.S. movie rental retailers. This company also collects the related rental information for the movies on a revenue-sharing basis. The data that we possess consist of the DVD rental turns and movie characteristics at the movie level from January 2001 to July 2005.

In addition to the movie-level data, we also collected consumer-level data from Netflix, a major U.S. online movie/TV series rental service with annual revenues in excess of $1 billion in 2008. The Netflix data set was made available to the public during the Netflix Prize competition, which offered $1 million to the team that could use the data to create the most accurate movie recommendation system. The data set consists of the movie ratings submitted by consumers through the Netflix web site from 2000 to 2005, from which we gathered the data from January 2001 to July 2005 to match with our movie-level rental data. Netflix encourages its users to rate the movies that they have watched both outside and within Netflix to improve its recommendations for them, so users have direct incentives to provide truthful and complete ratings. As a result, Shih et al. (2007) suggest that Netflix has the world's largest collection of movie ratings.

We believe that our data provide rich and strong evidence to study the impact of varying product variety on market concentration patterns. First, our rental data set is one of the most extensive source of information on the movie rental industry among all the related studies. Second, the revenue-sharing contract ensures the accuracy of the reported movie rental turns through considerable computer monitoring and external verification of the results. Finally, the data allows us to observe temporal changes in movie demand and the evolving customer preference. The combination of the two data sets allows doing so both at the movie and the consumer level, which is quite rare.

It is important to stipulate here that the online ratings data that we possess only reflect the number of movies rated, but not all customers rate all movies that they watch. On the other hand, customers do not have to watch the movie at Netflix to be able to rate it. Admittedly, using rating data as proxy for actual rental demand at Netflix can be inconclusive, but the rating data can provide insights into what movies consumers are aware of and are interested in. First, previous literature (see Chen et al. 2004) suggested a strong connection between product demand and the number of consumer reviews. In our own data, we find a correlation of about 0.5 between the monthly number of ratings and the rental turns among the matched movies. Second, unlike other review data that are known to have selection bias because users tend to review items they extremely like or dislike (see Hu et al. 2007; Dellarocas and Narayan 2007; Dellarocas and Wood 2008 and citations therein), pure ratings may avoid this bias because giving a rating is much less costly to a user than writing a review. In our data, we plot the histogram of the rating values on a scale from one to five and find the rating of four to be the most frequent, followed by the ratings of three, five, two and one. The bell-shaped histogram seems to suggest that Netflix users may be unbiased toward rating the movies that they extremely like or detest. Third, the recommendation system of Netflix directly incentivizes and facilitates its users to reveal their truthful and complete preference for movies to improve their recommendations. Finally, the movie-level results of the Netflix data endorse the main results of the rental data. For all these reasons, we proceed with utilizing ratings as proxy for the attraction of a movie and the consumer preference to complement the rental data at the consumer-level, although it should be understood that we imply the number of ratings.

Measures and Controls

In much of our analysis, we first elect to work with monthly (instead of weekly or yearly) data and therefore aggregate all variables at the monthly level. By doing so, we ensure both an adequate sample size in each month for each movie and enough observations over time for statistically significant estimates.

We are interested in studying varying demand for movies having different popularity levels. To reflect how popular movie j is at time t within a particular product offering set, we first rank the rental turns of each movie within each month in a descending order and use this rank as a proxy for movie popularity. Note that a higher (lower) rank indicates a less (more) popular movie. Then we propose two measures to categorize whether or not a movie is a hit. The first measure is the absolute ranking, e.g., the top 100, the top 1,000 movies, which is used in the previous literature including Anderson (2004). In this study, we define variable Hit_{jt} as a dummy variable, with one referring to movie j that ranks in the top 1,000 during month t and zero otherwise. Alternatively, we rank movies in relative terms, e.g., the top 10%, the top 20%, thus adjusting for current product variety (the total number of movies rented this month). Based on the relative rankings, we follow the A-B-C classification and classify the movies as follows: the movies that rank in the top 20% of all the movies rented that month are classified as Class A, i.e., highly popular movies. The movies that rank between top 20% and top 50% are classified as Class B. Finally, the movies that rank below top 50% are classified as Class C. For movie j during month t, we define a categorical variable $Class_{jt}$, with zero to be a Class A movie, one a Class B movie, and two Class C movie.

In addition, we define $Variety_t$ as the total number of different DVD movies that were rented during month t. Note that this variable reflects the active product variety as many movies are not rented in a given month. We believe that the active product variety is a more relevant variable than the total variety that includes DVDs with no rentals because 1) products that are not discovered by consumers (or that are discovered but forgotten) should not be taken into account when ranking popularity and 2) it accounts for both the product offering and consumer demand. Furthermore, we measure the demand for individual movies with a proxy $Share_{jt}$, which reflects movie j's market share of the rental turns among all the rented movies within month t. This measurement allows us to adjust for the possible change in the consumer base. To analyze the changing distribution of the cumulative demand, we also compute the monthly Gini coefficient $Gini_t$, which is often used in social sciences as a measure of inequality of a distribution (e.g., Yitzhaki 1979; Lambert and Aronson 1993). A $Gini_t$ of zero indicates total equality during month t, while a value of one suggests maximal inequality.

Finally, we consider a group of control variables about movie characteristics, which contain $Genre_j$ and $MPAA_j$. We also include a categorical variable $Trend_t$ to control for monthly characteristics. We further control for potential monthly demand auto-correlation by introducing one month lag of $Share_{jt}$ and $Gini_t$, which are classed $LagShare_{jt}$ and $LagGini_t$, respectively.

To summarize, all variable definitions at the movie level are presented in Table 1.

Table 1. Movie-level Analysis Variable Definitions

Variable	Definition
Hit_{jt}	Categorical variable, with one indicating a movie that ranks among the top 1,000 during month *t*, zero otherwise.
$Class_{jt}$	Categorical variable, with zero indicating that movie *j* is a Class A movie, one a Class B movie, and two a Class C movie during month *t*.
$Variety_t$	Total number of rented movies during time period *t*.
$Share_{jt}$	Share of the number of times that movie *j* is rented among all the rented movies during time period *t*.
$Gini_t$	The Gini coefficient of demand distribution during month *t*.
$MPAA_j$	Categorical variable of the MPAA rating of movie *j*.
$Genre_j$	Categorical variable of the genre of movie *j*.
$Trend_t$	Categorical variable of the 55 months in study.
$LagShare_{jt}$	One month lagged Sharejt.

In addition to the movie-level variables, we further define variables for our consumer-level analysis. We define $NicheSeeking_{it}$ as the average absolute ranking of the movies that consumer *i* rates in a given month *t*. In essence, $NicheSeeking_{it}$ is a summary statistics of the movie level popularity. A high value of $NicheSeeking_{it}$ means that this particular consumer *i* tends to watch more niche movies. We calculate the mean, the median, the top 10%, and the bottom 10% of the rankings to obtain more complete information about consumer choices. Furthermore, we divide these metrics by monthly product variety to obtain relative measurements. These relative measurements adjust for both the increasing product variety and the skewness of demand distribution.

In order to control for consumer heterogeneity over time, we define $FREQUENCY_{it}$ as the number of movies that user *i* rated in month *t*. In marketing, certain theoretical constructs such as the Dirichlet model suggest a strong link between purchase frequency and brand choice. In particular, it is often found that most consumers of a brand are low-frequency buyers (Chatfield and Goodhardt, 1975; Goodhardt et al., 1984). These light buyers often constitute the majority of the customers who purchase the popular brand (McPhee, 1963) because of the “super-star” effect (Rosen, 1981). In addition, McPhee (1963) explains that consumers who are familiar with the alternatives tend to consume the niche products. Therefore, consumers with high-consumption frequency are likely to consume more niche products than those with low-consumption frequency because the former may be better informed of the variety of products than the latter.

Furthermore, we define $RatingPropensity_{it}$ and $RatingVariance_{it}$ as the average and the variance of the ratings that user *i* gives in month *t*. These two measurements are likely to reflect people’s tastes and movie acceptance. For example Clemons et al. (2006) demonstrate the relationship between variance of ratings and demand for products. Further, Hu et al. (2007) recommend controlling for the standard deviation of ratings as well as for two modes to overcome consumer under-reporting bias. Since in our case the distribution of ratings is symmetric, we do not control for the modes. All user-level variables are defined in Table 2.

Table 2. Consumer-level Analysis Variable Definitions	
Variable	Definition
$NicheSeeking_{it}$	Popularity of the movies that user *i* rated in month *t*, measured as the mean and the median of the movie rankings, both in absolute and relative terms.
$Frequency_{it}$	Number of movies rated by user *i* in month *t*.
$RatingPropensity_{it}$	Average rating given by user *i* in month *t*.
$RatingVariance_{it}$	Variance of the ratings given by user *i* in month *t*.

Descriptive Statistics

Table 3 presents the descriptive statistics of the rentals by year. The product variety, which is the number of distinct movies available in the market, substantially increased from 7,279 in 2001 to 25,556 in 2005, up approximately two and half times. The total rentals also increased almost four times from 343 million turns in 2001 to 1.62 billion turns in 2004. As a result, the average rentals per title seems to also increase over time (from on 47,122 in 2001 to 69, 537 in 2004). For each title, the skewness of the turns increased from 8.5056 in 2001 to 19.5446, suggesting that the most popular movies are likely to contribute to an increasing market share. In addition, the minimum yearly turns per title dropped from 23 in 2001 to one in the following years. These descriptive statistics seem to suggest that the demand for movie rentals may become even more concentrated over time.

Table 3. Descriptive Statistics of Movie Rentals

Year	Product Variety	Total Rental (in Millions Turns)	Avg Turns per Title	Skewness of Turns	Min Turns	Median Turns	Max Turns
2001	7,279	343	47,122	8.5056	23	918	3,414,606
2002	11,013	672	61,019	10.2995	1	865	7,020,672
2003	15,713	1,060	67,460	12.1990	1	1,070	10,100,000
2004	23,297	1,620	69,537	14.4406	1	2,494	14,200,000
2005*	25,556	1,050	41,086	19.5446	1	1,577	14,500,000
Mean/year	16,572	949	57,245	12.9979	5	1,385	9,847,056
Stdev/year	7,809	478	12,582	4.2732	10	681	4,744,124

* We only observe seven months in 2005.

Figure 1 shows that the monthly product variety increased exponentially from January 2001 to July 2005 and that the rental turns increased linearly during the same period. A relevant question to ask is whether the product variety is growing because a lot of brand new movies are being released or because consumers keep discovering previously released titles. Our data indicates that the number of brand new titles increased from 2,504 in 2001 to 5,962 in 2004, while the newly rented back catalog titles decreased from 4,775 in 2001 to 4,032 in 2004. These observations suggest that the product variety growth is primarily due to introduction of brand new products. The more precise answer to this question is complicated by the fact that many movies are released on DVDs later than in theaters, but this gap continues to decrease over time. Further, most movies are released in several DVD versions at different points in time which makes it hard to exactly delineate rentals of "old" vs. "new" movies.

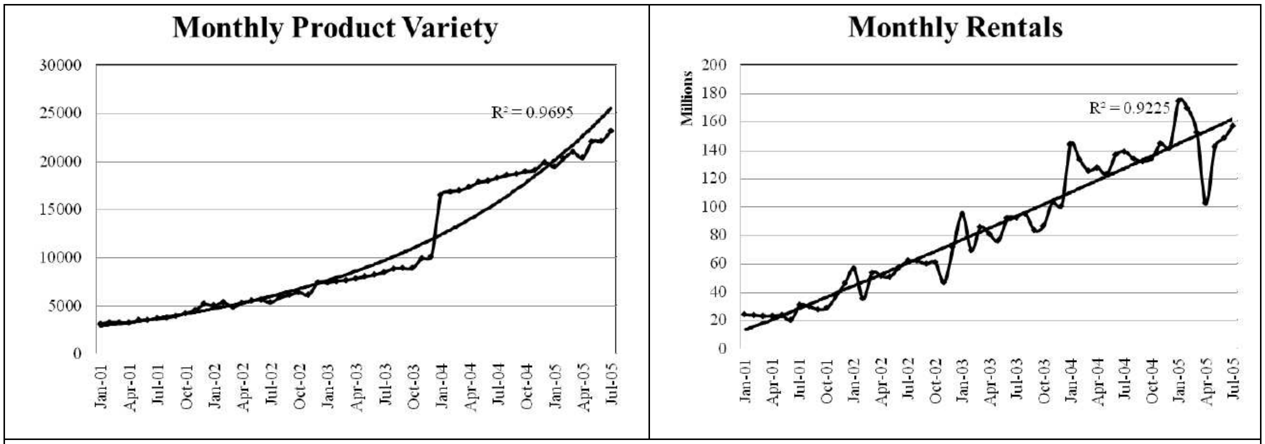

Figure 1. Monthly Product Variety and Rentals

Table 4 shows the summary statistics at the consumer level. The number of movies rated per person every month is highly skewed toward the high percentiles, indicating that a small group of people rate a large number of movies each month. It is possible that the large number of movies rated, such as 41 for 90th percentile and 219 for 99th percentile, contain a large number of ratings given by users to train the recommendation system because a user can only watch a limited number of movies every month. Ratings submitted during the training process can result in a "contamination" of the data because the ratings of previously watched movies may not reflect the current popularity of a movie. In order to alleviate this issue and provide a robustness check, we purged the data with the monthly number of rated movies more than 30. We choose the cutoff point of 30 because watching 30 movies a month is probably the maximum number of movies that a heavy user is technically allowed to watch within Netflix rental system. Our results remain qualitatively and quantitatively similar, so in the paper we report results without dropping any ratings.

Table 4. Descriptive Statistics of Movie Rentals

	Mean	Std	Skewness	1%	10%	25%	50%	75%	90%	99%
Number of Movies Rated	19	49	11	1	1	3	7	16	41	219
Average Rating	3.57	0.72	-.42	1.33	2.75	3.12	3.6	4	4.5	5
Variance of Ratings	0.70	0.64	1.42	0	0	0.22	0.6	1	1.55	2.88

Furthermore, it does not appear that heavy users have a tendency to give higher or lower ratings because the frequency of ratings very weakly correlates with the average rating (correlation = 0.0038) and with the variance of ratings (correlation = 0.1027). Figure 2 further shows that consumer ratings are almost normally distributed except that the right tail is censored at the rating of 5 because of the limit of the rating scale. This nearly normal distribution of consumer ratings provides statistical evidence that the users at Netflix may be unbiased toward rating the movies that they extremely like or extremely dislike. Furthermore, the variance of ratings is skewed, which suggests that the majority of the people tend to be consistent in their ratings.

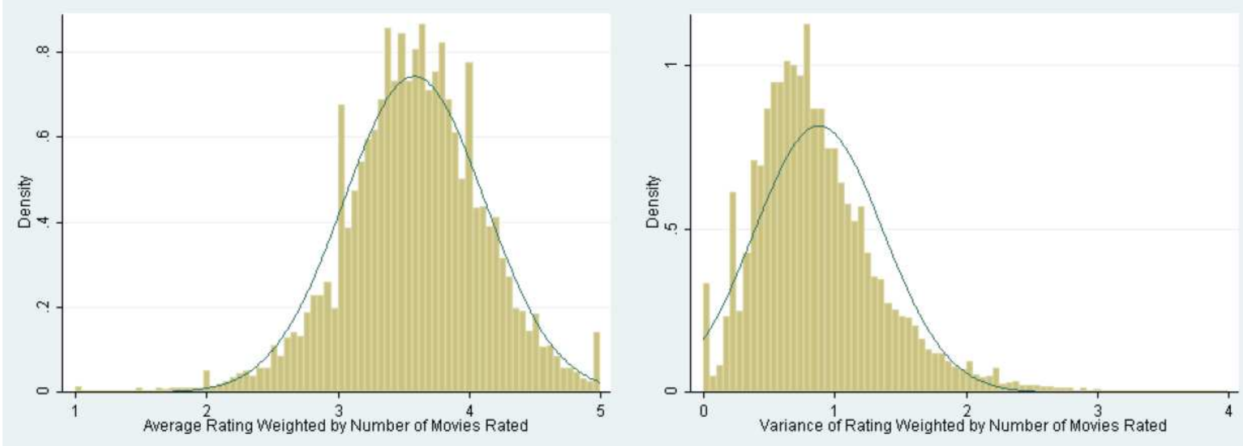

Figure 2. Monthly Rating Distribution

Estimation and Results

We test our hypothesis about the impact of product variety on demand concentration at two levels. First at the movie-level, we estimate regression models using three measures to examine the shift of demand concentration. We then use an instrumental variable approach to address the potential endogeneity issues. In order to gain insights into the movie-level analysis, we then turn our attention to examining the impact of product variety at the consumer-level. We employ fixed-effect models to understand how the propensity of each consumer to discover niche movies.

Movie-level Analysis

We use three different measures to comprehensively examine the changing demand concentration. We therefore specify the following three regression models:

$$\log(Share_{jt}) = \alpha_0 + \alpha_1 \log(LagShare_{jt}) + \alpha_2 Hit_{jt} \times Variety_t / 1000 + \alpha_3 Genre_j + \alpha_4 MPAA_j + \alpha_5 Trend_t + \varepsilon_{jt} \quad (1)$$

$$\log(Share_{jt}) = \beta_0 + \beta_1 \log(LagShare_{jt}) + \beta_2 Class_{jt} \times Variety_t / 1000 + \beta_3 Genre_j + \beta_4 MPAA_j + \beta_5 Trend_t + \xi_{jt} \quad (2)$$

$$Gini_t = \theta_0 + \theta_1 LagGini_t + \theta_2 Variety_t / 1000 + \upsilon_{jt}. \quad (3)$$

In these three models, we divide $VARIETY_t$ by 1,000 and logarithmically transformed $Share_{jt}$ for interpretation purpose. Models (1) and (2) are also referred to as moderation models, which have been widely used in behavioral and social sciences to understand the implicit nature of the relationship between the dependent and independent variables (Baron and Kenny, 1986; Muller et al., 2005). These models assume that the effects of independent variable, i.e., $Variety_t$ are moderated by moderators, i.e., Hit_{jt} and $Class_{jt}$, causing different marginal effects for movies having different popularity levels.

Although the regressions above provide a useful preliminary and exploratory analysis (Kennedy, 2003), they may be biased by the potential endogeneity of $Variety_t$. Retailers tend to stock product variety based on sales forecast, thus causing Share, *Gini* and *Variety* endogenous. Other unobserved confounding factors, such as movie's intrinsic quality may also cause omitted variable bias in estimating the dependent variables. In order to address these potential endogeneity and omitted variables issues, we adopt an instrument variable 2SLS approach (Angrist and Krueger, 1994). The 2SLS instrument estimator can provide consistent estimate of the dependent variables. It is also quite robust in the presence of other estimating issues such as multicollinearity. In addition to its relative low computation cost, the 2SLS instrument variable approach is widely used to address the endogeneity issue (Kennedy, 2003).

A valid instrumental variable should satisfy relevance and exclusion restriction assumptions (Wooldridge, 2002). In particular, it should be uncorrelated with the error (i.e., exclusion restriction) and correlated with the endogenous regressor (i.e., relevance). In other words, the instrument should explain the outcome variable only through the endogenous regressor. We propose using the lagged value of the independent variable as a candidate for valid instrument. In particular, we compute $Variety_{t-1}$, previous month's product variety to use as an instrument for the current month. We expect this lagged Variety is exogenous because the product variety one month ago should not determine the unobserved factors for the demand during the current month. In other words, the lagged variable is not contemporaneously correlated with the disturbance (Kennedy, 2003), so it should satisfy the exogenous restriction assumption of a valid instrument. Moreover, we expect that the lagged Variety is correlated with the current *Variety* and therefore satisfy the relevance assumption because retailers generally consider their previous product assortment to assort movies for the current period.

The results of movie-level analysis are shown in Table 5. The left pane shows the results of the absolute popularity measure. The coefficients of *Variety* are significantly negative in both models (-0.0047 and -0.0048), which suggest that product variety has an negative impact on the demand for those movies that rank outside of top 1,000 movies per month, i.e., niche movies. Interpreting the coefficients of the 2SLS model, we find that an increase of 1,000 movies per month is likely to result in -0.47% decrease in market share for an average non-hit movie. In contrast, the coefficients of *Variety* for hit movies are consistently positive (-0.0047+0.0188=0.0141;-0.0048+0.0189=0.0141), suggesting that product variety has a positive impact on the demand for those movies that rank within top 1000 movies per month, i.e., hit movies. In particular, an increase of 1000 movies per month is likely to increase the market share for an average hit movie by 1.41%.

The middle pane shows the results of the relative popularity measure. The coefficients of *Variety* are positive across the two models (both coefficients equal 0.0097), which imply that an increase of 1000 movies in the monthly product variety is likely to increase the demand for a movie that ranks within top 20% of all the movies in that month, i.e., a Class A movie, by 0.97%. However, the demand for Class B and Class C movies decreases in product variety. The coefficients of *Variety* for Class B movies are equal to -0.0174 in both models (0.0097-0.0271=-0.0174;0.0097-0.0271=0.0174), which suggest that an increase of 1,000 new movies per month may reduce the demand for an average Class B movie by 1.74%. The negative demand impact of product variety is even stronger for Class C movies. The coefficients are about -0.048 in both models (0.0097-0.0579=-0.0482;0.0097-0.0577=0.048), which implies that an increase of 1000 new movies per month may reduce the demand for an average Class C movie by 4.8%.

The right pane presents the results of the Gini Coefficient measure. The coefficients of *Variety* are significantly positive across the two models (0.0015 and 0.0013), suggesting that product variety is likely to enlarge the demand inequality. In particular, 1,000 new movies are likely to increase the demand inequality by about 0.13%.

So far, confirming our hypothesis, the analysis of all three measures shows consistent results across models that product variety is likely to increase the demand for hit movies and decrease the demand for niche ones. The coefficients of other control variables are within our expectation and we omit to report them because of page limit.

Table 5. Movie-level Analysis Results

	Absolute Measure		Relative Measure		Gini Coefficient	
	Model (1)	2SLS	Model (2)	2SLS	Model (3)	2SLS
VARIETY	-0.0047	-0.0048	0.0097	0.0097	0.0015	0.0013
	(-5.3994)***	(-6.4445)***	(11.0683)***	(13.7434)***	(5.0056)***	(4.1310)***
Variety × (Hit=1)	0.0188	0.0189				
	(51.5364)***	(82.8822)***				
Variety × (Class=B)			-0.0271	-0.0271		

			(-82.2646)***	(-156.8923)***		
Variety × (Class=C)			-0.0579	-0.0577		
			(-113.9049)***	(-241.9799)***		
LagShare	0.9163	0.9161	0.8211	0.8214		
	(1129.8332)***	(1913.4299)***	(589.5139)***	(1381.7800)***		
LagGini					0.2168	0.3099
					(1.6114)	(2.2795)*
Genre	Yes	Yes	Yes	Yes		
MPAA	Yes	Yes	Yes	Yes		
Trend	Yes	Yes	Yes	Yes		
Hypothesis Supported	Yes	Yes	Yes	Yes	Yes	Yes
Observations	498,111	498,111	498,111	498,111	54	54
Adjusted R^2	0.938	0.938	0.945	0.945	0.777	0.774
1) * p-value<0.05, ** p-value<0.01, ***p-value<0.001						
2) The rows below the estimates are t statistics.						

Consumer-level Analysis

Consistent with the rental data results, the movie-level analysis of Netflix data shows that product variety is positively associated with the demand for hit movies and negative associated with niche ones. We now turn to the Netflix data to understand how individual consumers change their preference for movies over time in order to gain insights into the movie-level analysis. In particular, we examine how the propensity of each consumer to discover niche movies evolves, while controlling for observed user heterogeneity, such as rating frequency and variance of ratings. The data that we have lacks other potentially significant consumer characteristics, such as demographics. In order to cope with this issue, we introduce a time-invariant preference for each consumer's movies through the panel data analysis and we further assume that the preference correlates with the observed characteristics of the consumer. This correlation is likely to be caused by the recommendation systems, which can influence an individual's preference based on his/her observed characteristics. The Hausman test further provides strong evidence of this correlation. Therefore, we employ the following fixed-effect regression to predict consumer propensity to rate movies:

$$\log(NicheSeeking_{it}) = \beta_0 + \beta_1 Variety_t / 1000 + \beta_2 Frequency_{it} + \beta_2 RatingPropensity_{it} + \beta_3 RatingVariance_{it} + \mu_i + \varepsilon_{it}. \quad (4)$$

The top of Table 6 shows the results of the absolute movie rankings while the bottom presents the same results of relative movie rankings using Model (4). As is evident from the top of the table, all $Variety_t$ coefficients are significantly positive, suggesting that the absolute popularity rankings of the movies watched by the average consumer consistently increase. In other words, consumers tend to discover more and more niche movies over time when movies are ranked in absolute terms. In particular, the $Variety_t$ coefficient for the bottom 10th percentile of the movies that a person rates (i.e., the obscure titles) is 0.0519, which is approximately 30 times as much as the same coefficient for the top 10th percentile of the movies (i.e., the popular titles). This comparison suggests that consumers are likely to discover niche products much faster than they move away from the hits (again, if popularity is measured in absolute terms).

However, the picture completely changes when the popularity of the movies is measured in relative terms. The bottom part of Table 6 shows that $Variety_t$ coefficients are consistently negative, suggesting that, relative to the product variety that is available at that point of time, consumers tend to be interested in more and more popular movies. In particular, the $Variety_t$ coefficient of the top 10th percentile of movies is -0.0919, which is over twice as much as the coefficient of the bottom 10th percentile of movies, suggesting that a consumer's attention shifts toward more popular hits faster than it shifts away from less popular niches. Taken together, the results of Model (4) suggest that the growth rate of product variety is substantially higher than the speed at which consumers discover niche products. This finding is consistent with the results of Fleder and Hosanagar (2009) that recommendation systems guide similar consumers to the same products, which does not effectively help consumers discover products at the tail of the distribution.

Table 6. Fixed-Effect Model of Nicheseeking Behavior

	Mean	Median	Top 10%	Bottom 10%
Variety	0.0519	0.0432	0.0017	0.0519
	(230.8361)***	(172.6778)***	(5.1988)***	(207.5826)***
Frequency	0.0007	0.0009	0.0029	0.0009
	(56.7948)***	(63.6386)***	(151.8274)***	(58.8934)***
RatingPropensity	-0.1146	-0.1563	-0.2609	-0.0737
	(-114.6938)***	(-140.7099)***	(-181.2741)***	(-66.3571)***
RatingVariance	0.2559	-0.0056	-0.6601	0.5156
	(247.2793)***	(-4.8660)***	(-442.8767)***	(448.3906)***
Overall R^2	0.031	0.012	0.048	0.059
	Relative Mean	Relative Median	Relative Top 10%	Relative Bottom 10%
Variety	-0.0414	-0.0504	-0.0919	-0.0417
	(-181.8804)***	(-201.1105)***	(-282.9875)***	(-166.6757)***
Frequency	0.0006	0.0009	0.0028	0.0008
	(48.8355)***	(62.6628)***	(150.8515)***	(58.0375)***
RatingPropensity	-0.1184	-0.1544	-0.2590	-0.0718
	(-116.9729)***	(-138.7156)***	(-179.5866)***	(-64.6588)***
RatingVariance	0.2440	-0.0064	-0.6609	0.5148
	(232.8270)***	(-5.5547)***	(-442.4297)***	(447.4733)***
Overall R^2	0.030	0.016	0.064	0.062
Observations	4,740,731	4,740,731	4,740,731	4,740,731
1) * p-value<0.05, ** p-value<0.01, *** p-value<0.001				
2) The rows in parentheses are t statistics.				

Furthermore, the consistently positive and highly significant coefficients of $Frequency_{it}$ indicate that heavier users tend to discover more niche movies. In particular, the coefficients for both absolute and relative means are about 0.0006 and for both medians are 0.0009. In other words, if an average consumer watches five more movies per month, the mean of his/her propensity for niches is likely to increase by 0.3% on average. Accordingly the median is likely to increase by 0.45% on average, holding other factors constant. Thus, it appears that heavy users are the ones that drive toward the demand for niche products, which can cause Long Tail effect. Nevertheless, these heavy users constitute a relatively small segment of the entire population: as we demonstrated earlier, heavy users with a monthly frequency over the mean constitute less than 25% of all users. Although this small group of people tends to discover more niche movies, it does not seem to shift the entire demand from hits to niches. A comparison of coefficient for the top 10th percentile (0.0028) and coefficient for the bottom 10th percentile (0.0008) suggests that heavier users shift away from the hits approximately three times as fast as they discover niches. That is, even heavy users are not as fast in discovering niches as they are in "forgetting" about hits.

Consistently negative and highly significant coefficients of $RatingPropensity_{it}$ suggest that consumers who, on average, give higher ratings and may therefore be more satisfied tend to be interested in more popular movies. For example, the coefficients for both absolute and relative means are around -0.11, which suggests that increasing the average rating by one unit is associated with a 11% increase in the average movie popularity. In other words, the more popular movies generally satisfy people better than the obscure titles. Of course, it is possible that consumers who watch popular movies are systematically different from consumers who watch niche movies in that the former tend to rate all movies higher than the latter. Since we are unable to observe characteristics of individual consumers, our finding is subject to this limitation.

Finally, we note that $RatingVariance_{it}$ is negatively associated with the median and the top 10th percentiles, while this variable is positively associated with the mean and the bottom 10th percentiles (in either absolute or relative terms). We interpret these mixed signs to imply that consumers having highly disperse rating tend to watch extreme hits and niches. In other words, the extreme hits and the extreme niches receive more polarized ratings from those consumers. Further, the popularity of the movies that those consumers watch trends to skew toward the niches. In other words, consumers having highly disperse ratings watch a larger quantity of hits than niches, but the niches that they watch are generally extremely obscure.

Conclusion and Discussion

Previous studies about the Long Tail effect implicitly assume that expanding product variety will satisfy consumer's increasingly heterogeneous tastes, thus causing the demand for niches to rise. In this paper we empirically examine the impact of product variety on demand concentration. We use two large data sets from the movie rental industry and analyze the data at both movie-level and consumer-level. We employ multiple measures to understand the changing demand concentration and consider the potential endogeneity of product variety. Unlike the previous assumption, multiple model analyses in our study consistently suggest that product variety is likely to increase the demand for hits and yet decrease the demand for niches.

It is true that product variety tends to increase across industries particularly in the Internet age. It is equally true that more and more products can be left unnoticed by consumers, or are being discovered very slowly, even though the customer base is also expanding. In order to gain insights into those movie-level findings, we further examine changes in the demand distribution at the consumer level. Once again, we find that product variety indeed diversified consumers into more niche movies in absolute terms, but we also discover that the rate at which consumers shift demand from the hits to the niches is considerably lower than the growth rate of product variety. Therefore, if we normalize demand for currently active product variety and measure popularity in relative terms, we find that consumers tend to watch more and more hits as product variety grows. In other words, expanded product variety may threaten the attraction of one movie by Tom Cruise because of demand diversification, but it may favor more and more movies by Tom Cruise-like celebrities.

Figure 3 visually illustrates the comparison between the absolute and relative popularity of the movies that consumers watch. In Figure 3 (left, bottom line), we observe the median movie that the average consumer discovers over time, which has a linear upward trend, indicating that consumers increasingly discover niches. In particular, at the beginning of our study, the median movie rated by an average consumer was ranked slightly above 350, while at the end of the study the median movie ranking had increased more than twice to over 850. However, Figure 3 (left, top line) also indicates that product variety increased even faster, which creates an impression of the lengthening tail of demand distribution: there are more and more obscure movies over time. However, once we bring distribution to the common scale through dividing by current product variety, the claim of the increasing demand for niches disappears. Not surprisingly, Figure 3 (right) shows that, when we look at the median popularity in relative terms, the average consumer gravitates more and more toward hits. In fact, at the beginning of our study the average consumer are interested in the movies in the 10th percentile of product variety while at the end of the study the average consumer is interested in the movies in the 6th percentile. Hence, we conclude that although consumers do venture into niches, new movies appear more quickly than people can actually discover them.

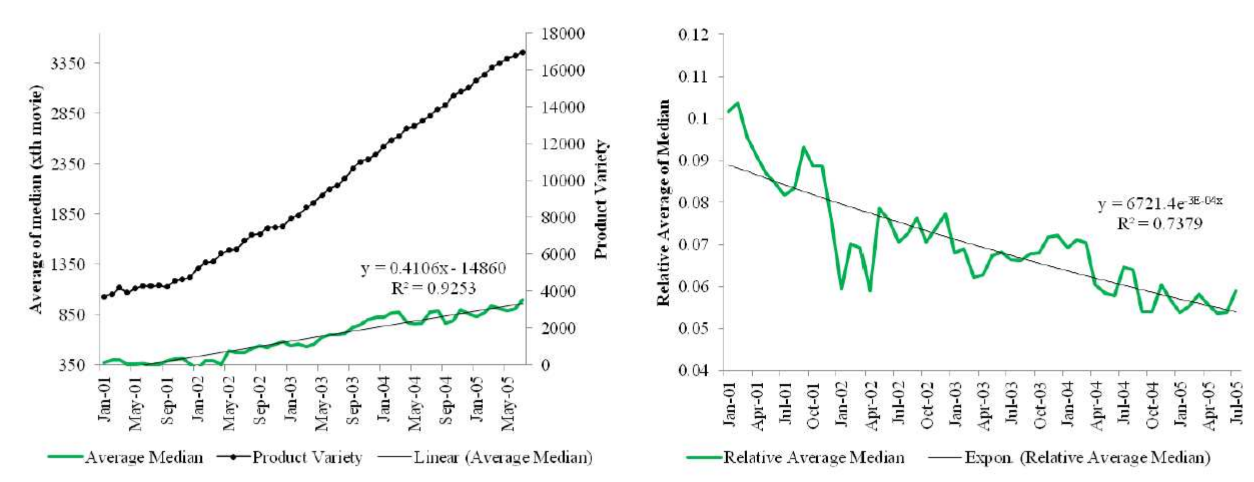

Figure 3. Average Median and Relative Average Median Popularity

We make a number of additional observations based on our consumer-level analysis. We find evidence that the consumers who give high average ratings tend to watch more popular movies. Hence, we do not find any evidence that niche products satisfy consumer tastes better and better over time, which is suggested by Anderson (2004; 2006). Furthermore, we find that the consumers who discover the niches tend to be heavy users, constituting only a small part of the entire user base. Light users, however, tend to focus on the popular items and since most users are in this category, hits continue to drive the market.

Our findings have a number of managerial implications as they shed new light on the controversy surrounding the Long Tail effect. First, the promise of the Long Tail effect became a basis for many new business models and business ideas (Anderson, 2006). Our findings suggest that caution needs to be used when assessing the potential benefits of focusing a business on supplying niche products. While it may be true that niche products are much more profitable for companies (e.g., Anderson 2006 rightfully suggests that niche movies cost a fraction of hit movies to make), this argument does not account for the fact that for each niche product that consumers demand, there might be several that are never discovered, thus potentially adding to the costs but not to the revenues. Irrational expansion into niche products will also increase operational difficulties, such as maintaining the level of service (Fisher et al., 1994; Randall and Ulrich, 2001). In fact, to compete against Netflix-like companies that stock a large product variety of niche movies, companies like Redbox successfully remain profitable by focusing only on a selected number of hit movies. In addition, Amazon.com, which is often cited as an example of offering numerous long tail products on its platform, is found to directly sell only a small percentage of all products listed on its website, with the most products being sold by third-party sellers because of insufficient demand for those niche products (Jiang et al., 2011).

Further, a large number of products might take a while to be discovered. This finding seems to suggest that much more attention needs to be paid to recommendation systems, review forums and other means of aiding product discovery. Although Netflix employs what is widely considered to be a sophisticated recommendation system, even this system does not allow numerous consumers to discover titles as fast as they appear. This raises an important issue of carefully forecasting how long will it take for a given title, once it is added to the inventory, to begin accumulating demand. More improvements to the recommendation systems, such through the Netflix Prize and the algorithm proposed by Park and Tuzhilin (2008) should be implemented.

Insights from our consumer-level analysis suggest that consumers are generally much more satisfied by hit products than by niches. This is an important consideration: while Netflix currently achieves extremely high customer satisfaction, we do not find any evidence to suggest that customers watching obscure titles find them more satisfactory than other movies. We can speculate that many consumers over time will learn that niches are called niches for a reason and might start ignoring them altogether. Our other observation that heavy users tend to venture into more obscure movies suggests that the presence of the Long Tail effect might be moderated by the frequency of service. In the case of Netflix, it is physically impossible to rent more than a few DVDs per month (due to the time that the mailing process takes). However, Netflix and other companies (such as Amazon.com and Hulu.com) have started allowing customers to watch DVDs on their computers at home right away, which may increase the number of heavy users who discover niches. In this case, one will have to re-examine the demand concentration.

It is important to remember the limitations of our findings. First, our study does not directly compare the search costs between brick-and-mortar and Internet companies (e.g., Brynjolfsson et al. 2011) and therefore we are unable to comment on this aspect of the Long Tail effect. Rather, our findings need to be interpreted as a study about the impact of product variety on demand concentration only. Comparing the effects of product variety across channels would be of considerable interest for research. Second, our study has focused on the movie rental industry. It is possible and worthwhile to confirm that demand concentration in other product categories may respond differently to the varying product variety levels. Third, our consumer-level analysis is restricted to the ratings data. To address this issue, we confirm that the main results of rental data are consistent with those of the ratings data and we use the consumer-level rating data to offer additional insights into the movie-level analysis. Admittedly, the consumer-level results cannot be taken as exact evidence for individual rental behavior on Netflix.com. Some consumers probably do not rate the movies that they watched. Nevertheless, consumers also rate movies that they watched elsewhere, providing a richer picture of demand for movies which reflects interest, attention and satisfaction. An interesting venue for research, particularly for behavioral economics, would be to compare ratings data with time-stamped individual-level rental data to understand possible rating behavior biases. In addition, the data set with the time-stamped individual-level information may be potentially used to study consumer purchase patterns and their life-time value.

Further research opportunities also include linking recommendation system metrics, such as product ratings, with operations management and marketing strategies (see Netessine et al. 2006 for some initial work in this direction) is also a fruitful direction. Finally, incorporating the empirical findings of the product variety effects on demand concentration and evolving consumer preferences into the analytical models, such as dynamic assortment (Caro and Gallien, 2007) is highly warranted.

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