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DOCTORAL DISSERTATION

ESSAYS ON CHANNELS AND PRODUCT LINE DESIGN

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Pak Yan Choi

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Abstract

In the first chapter I talk about the estimation of the degree of substitution and complementarity in DVD/Blu-ray and theatrical channels. Movies are distributed through multiple, carefully segmented channels. Movies are first released in theaters, and then released in home entertainment products. In recent years, movie studios have been pushing to expedite the release of DVD/Blu-ray discs and home videos at the expense of theaters. However, sacrificing the theatrical channel might backfire if additional theatrical viewership would have exerted a strong promotional influence on subsequently released home entertainment products. To estimate the causal effect of additional theatrical viewership on home entertainment product demand, we leverage snowstorms' adverse impact on consumers' propensities to watch a movie in theaters. Exploiting this source of exogenous variations in theatrical viewership with a nonparametric simultaneous equations model, we find that additional theatrical viewership has a positive and economically substantive impact on the sales of home entertainment products. This finding indicates that the promotional effect outweighs cannibalization. In other words, the theatrical channel is a complement to the home entertainment channel. We also find that the degree of complementarity is weaker for horror movies and stronger for family-oriented movies, suggesting that a movie's suitability for gifting and appeal for repeated consumption are important moderating factors. Our finding that theaters complement home entertainment products challenges the conventional wisdom in the movie industry and cautions against a drastic quickening of DVD/Blu-ray disc and home video releases.

In the second chapter I discuss the estimation of the effect of piracy on worldwide theatrical demands and its implication for international release scheduling. International markets have become a significant contributor to Hollywood movie revenue in recent years. Widespread adoption of new projection technology has enabled movie studios to be flexible in setting their international movie release schedules. However, decisions about the timing of international releases are complicated by piracy. For example, releasing a movie earlier in Russia might boost box office revenue from Russia, but on the other hand it

might quicken the circulation of a pirated copy originating from Russia, because pirates can tape the released movie in theaters. In turn, as pirated videos can be distributed online and consumed worldwide, the potential increase in piracy due to early release in Russia might cannibalize box office demands in other countries. In order to properly account for the effect of global cannibalization across geographic markets from piracy on the scheduling of global releases, I estimate both the timing and prevalence of piracy supply by country and the varying degrees of substitution from theatrical demand to pirated videos in different languages for seven major countries.

In the third chapter I discuss product and product line design in the context of product colors. When choosing which colors to offer in their product lines, firms often rely upon consumer preference models that do not account for the heterogeneity of their target market and do not consider the trade-offs consumers are willing to make for different color options. For this research we used visual conjoint analysis to assess preference for backpack color and then modeled respondent utilities with a Bayesian hierarchal multinomial logit model. This provided counter intuitive results in which product line color options are not additive but each color changes depending on the number of options the firm is willing to offer and that colors which seem to dominate secondary preferences within a target market may not be the best colors to choose for product line expansion.

Table of Contents

Chapter 1

Chapter 1: Do Movie Theaters Cannibalize or Complement Home Entertainment Products? Evidence from a Natural Experiment

Movies are distributed through multiple, carefully segmented channels. Movies are first released in theaters, and then released in home entertainment products. In recent years, movie studios have been pushing to expedite the release of DVD/Blu-ray discs and home videos at the expense of theaters. However, sacrificing the theatrical channel might backfire if additional theatrical viewership would have exerted a strong promotional influence on subsequently released home entertainment products. To estimate the causal effect of additional theatrical viewership on home entertainment product demand, we leverage snowstorms' adverse impact on consumers' propensities to watch a movie in theaters. Exploiting this source of exogenous variations in theatrical viewership with a nonparametric simultaneous equations model, we find that additional theatrical viewership has a positive and economically substantive impact on the sales of home entertainment products. This finding indicates that the promotional effect outweighs cannibalization. In other words, the theatrical channel is a complement to the home entertainment channel. We also find that the degree of complementarity is weaker for horror movies and stronger for family-oriented movies, suggesting that a movie's suitability for gifting and appeal for repeated consumption are important moderating factors. Our finding that theaters complement home entertainment products challenges the conventional wisdom in the movie industry and cautions against a drastic quickening of DVD/Blu-ray disc and home video releases.

1.1 Introduction

The marketing environment for motion picture content has changed significantly in recent years. While movies are almost always released first in theaters and later in home entertainment formats such as DVD/Blu-ray discs, the importance of these home entertainment channels has increased significantly over time, both in terms of revenue and consumer interest. For example, theatrical revenue made up 55 percent of a typical movie's revenue in 1980, but only 20 percent in 2007, with the remaining 80 percent coming from home entertainment releases (Epstein 2012). In terms of consumer interest, a 2005 Ipsos survey found that only 22 percent of Americans surveyed would prefer to see a movie in a theater versus watching the same movie at home on DVD (Keating 2012). More recently, theatrical attendance hit a two-decade low in 2014 (McClintock 2014), the same year that ticket prices hit an all-time high (Linshi 2015). The increasing importance of the home entertainment window is also reflected in the changing marketing environment for home entertainment content, notably the reduced delay between average theatrical and DVD release dates, which declined from just under 6 months in 1998 to just under 4 months in 2013 (Ulin 2013) (see Figure 1.1 for a summary of a movie's release timeline). The push to expedite the release of home entertainment products has caused tension between movie studios and theaters. When Disney announced its plan to release *Alice in Wonderland* in DVD/Blu-ray 12 weeks after the theatrical opening, a number of European exhibitors threatened to boycott the movie. In 2014, the four largest theater chains in the U.S., the largest exhibitor in Canada, and Europe's second largest exhibitor boycotted the sequel of *Crouching Tiger, Hidden Dragon* because The Weinstein Co. signed a deal to release the movie simultaneously in theaters and on Netflix.

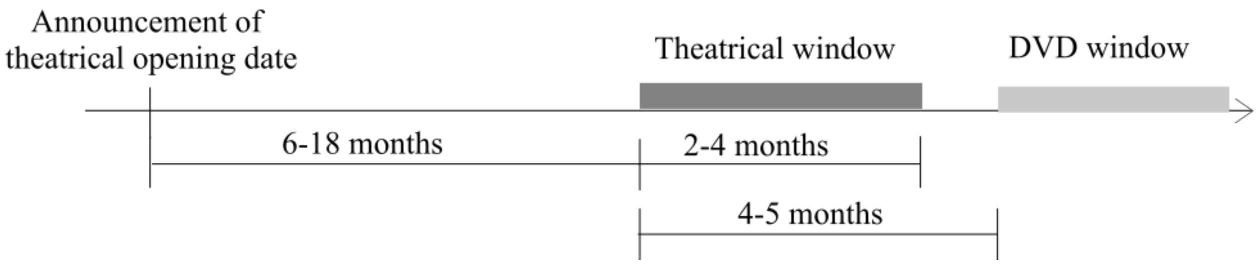

Figure 1.1 Timeline of the announcement of the theatrical opening date, the theatrical window, and the DVD window in the United States

Given these changes in the marketing environment of the motion picture industry, it is important for managers to understand the interactions between theatrical and home entertainment channels. This paper examines the role of the theatrical channel among distribution channels in the motion picture industry by testing the hypothesis that there is a demand spillover from the theatrical channel to subsequent home entertainment channels with field data. If this hypothesis is true, then an additional moviegoer in the theater is worth more than the movie ticket revenue to the movie studio, and the studio should be cautious in adopting strategies that would encroach on the theatrical channel.

Additional moviegoers may exert positive effects on the demand for home entertainment products. One key mechanism behind this cross-channel positive effect relates to social influence. After watching a movie in theaters, moviegoers may share their experience with their social circles. Increased awareness of the movie among the community can raise the demand for DVD/Blu-ray. Another key mechanism relates to multiple-purchases (Hennig-Thurau, Henning, Sattler, Eggers, and Houston 2007). Some consumers buy DVD/Blu-ray discs for rewatch or for gifts after they have watched the movie in theaters. The theatrical experience reveals valuable information about the quality of the movie and about how well the movie matches the taste of the moviegoer, and consumers may be more likely to buy the DVD/Blu-rays of the movies that they have less uncertainty. In the rest of the paper, we refer to the positive influence of theatrical attendance on home entertainment demands as the “domino effect.” If this domino effect is stronger than the cannibalization of theaters by home entertainment channels, then theaters are a complement to home entertainment products. In this case, drastically expediting the release of home entertainment products may be suboptimal for movie studios. A strong domino effect means that the moviegoers have a significant positive spillover on the demand for home entertainment products; however, shortening the time-to-release in home entertainment channels causes some consumers to switch from the theatrical channel to home entertainment channels. In turn, the lowered theatrical attendance can have a negative effect on home entertainment demands, due to the reduction in positive cross-channel spillover. Ahmed and Sinha (2016) find that it is optimal for movie studios to increase the time lag from theatrical release to DVD release to maximize total revenue from the two channels. A strong domino effect of theatrical channel on home entertainment channels would be a plausible explanation for their finding.

In this regard, although it is well known that a movie's theatrical revenue is a strong predictor of its subsequent home entertainment revenue, there is no rigorous empirical evidence indicating whether increased theatrical attendance causes an increase in home entertainment demand. From a theoretical standpoint, theatrical attendance could have either effect: To the extent that consumers perceive the theatrical experience to be relatively undifferentiated from watching a DVD or Blu-ray disc at home, one would expect that the two channels would be substitutes—with increased consumption in one channel reducing demand in the other channel. However, if the channels are significantly differentiated and if there is a strong domino effect, then complementary forces would outweigh the cannibalizing force. To the best of our knowledge, there is no empirical research that estimates the magnitude of these complementary effects from field data. Therefore, whether the complementary forces for theatrical consumption on downstream home entertainment channels can outweigh the cannibalization remains an open question.

However, empirically testing whether theatrical viewership has a positive or negative impact on demand in subsequent distribution channels is challenging. Using observed theatrical admission and DVD/Blu-ray sales data to test the impact of theatrical attendance on DVD/Blu-ray demand at a movie level suffers from obvious endogeneity problems: unobserved movie popularity factors impact both theatrical demand and home entertainment demand in ways that available control variables do not capture. Because movies with superior popularity factors have higher demand in both theaters and home entertainment formats, analyses that do not account for these unobserved confounders would incorrectly attribute this correlation in demand to the effect of theatrical viewership on the demand for DVD/Blu-ray releases. To accurately test whether theatrical viewership has a causal impact on subsequent DVD/Blu-ray sales, we need an exogenous shock to theatrical viewership. Exogenous shocks introduce changes to theatrical viewership that are independent of all unobserved factors, and thus enable us to identify how changes in theatrical viewership affect subsequent DVD/Blu-ray sales.

In this paper, we use major snowstorms surrounding a movie's opening weekend as just such an exogenous shock. Major snowstorms impede travel and reduce theater attendance. The negative correlation between snowstorm occurrences and theatrical viewership, coupled with the random and unpredictable nature of snowstorm occurrences, produces plausibly exogenous variations in theatrical viewership across geographic markets for movies released in the winter. We then use this exogenous variation in theatrical attendance to determine how lower theatrical attendance in a particular geographical region impacts demand in the subsequent DVD/Blu-ray release window.

Our results show that theatrical demand causally increases home entertainment demand. Specifically, a 10% increase in theatrical attendance would boost the DVD/Blu-ray demand by 2.4%. This suggests that the complementary forces outweigh the cannibalization in these two channels. We also find similar results in the iTunes rental channel. In summary, we find empirical evidence that the theatrical channel has a significant domino effect on demands for home entertainment channels; thus, the theatrical channel is a complement to home entertainment channels. Furthermore, we determine that the degree of complementarity is strongest in family-oriented movies and weakest in horror movies.

1.2 Literature

Our research is related to a number of papers in the academic literature analyzing movie sales in the theatrical and home entertainment windows. For example, Lehmann and Weinberg (2000) specify a model that uses observed theatrical sales to predict video rentals in the home entertainment channel. Their paper specifies exponential curves for both theatrical sales from the theatrical channel and from the video rental channel. However, it is important to note that their paper focuses on predicting rental sales, not on establishing a causal relationship between theatrical attendance and video rentals. Thus, because their paper does not account for unobserved confounders that affect demand in both distribution channels, it does not establish that a change in theatrical attendance would lead to a change in demand in subsequent home entertainment channels.

In a related study, Mukherjee and Kadiyali (2011) model the demand for DVD purchases and DVD rentals. Our paper differs from their study in that the two channels modeled in Mukherjee and Kadiyali (2011) overlap and, thus, consumers make simultaneous consumption decisions for the two channels, whereas the channels considered in this paper and Lehmann and Weinberg (2000) are separated temporally, allowing for sequential consumption decisions. Mukherjee and Kadiyali (2011) share a limitation similar to that in Lehmann and Weinberg (2000)—that unobserved demand shocks, such as unobserved movie popularity factors, confound their results. Neelameghan and Chintagunta (1999) model the box office performance of the U.S. and international theatrical channels. They specify that viewership in each channel follows a Poisson distribution, and then link the mean parameters to control variables and movie characteristics in a hierarchical Bayesian specification. Again, unobserved movie popularity factors not fully explained by the control variables and observed movie characteristics would confound any conclusion on the substitution or complementarity nature of the channels. Finally, in an analysis of the advertising responsiveness in the U.S. DVD market, Luan and Sudhir (2010) report that a 0.96% increase in DVD sales is associated with a 1% increase in the box office. Because their modeling approach is designed to handle the endogeneity issues in advertising spending, DVD release lag, and DVD retail price, the model does not adequately resolve the endogeneity problem in the box office for the determinant of DVD sales caused by omitted confounders. Therefore, the positive association between box office and DVD sales reported in Luan and Sudhir (2010) does not establish that the two channels are complementary.

Ahmed and Sinha (2016) apply copulas to jointly model revenues of theatrical and DVD channels to optimize the timing decision of DVD releases. A key feature of their model is that it assumes consumers may choose to consume in both theaters and DVD channels, and does not impose a prior assumption on how the decay of sales in the DVD channel vary over time. They find an inverted U-shape relationship between studios' revenue and the time-to-DVD release, and therefore find that movie studios' optimal strategy is to adopt a moderate delay in DVD release. An important contribution of our paper is to provide empirical evidence that preceding theatrical attendance has a *causal* effect on demands for subsequent home entertainment channels, and this causal cross-channel spillover effect can explain the inverted U-shape revenue relationship found in Ahmed and Sinha (2016).

Our study is also related to the following studies that analyze movie distribution in multiple sequential channels. Hennig-Thurau et al. (2007) suggest that a multiple-purchase effect, an information-cascading effect, and an uninformed-cascading effect can cause a potential complementarity between the theatrical channel and home entertainment channels. A multiple-purchase effect means that consumers see a movie more than once, and their theatrical viewing stimulates the purchase in subsequent channels. An information-cascading effect means that the success of the theatrical channel affects the performance of subsequent channels, through shared personal experience such as word-of-mouth. An uninformed-cascading effect means that the success of the theatrical channel affects the performance of subsequent channels through aggregate facts, such as released box office numbers. Calzada and Valletti (2012) constructed a game-theoretic model of movie distribution and consumption. An important implication of their model is that the optimal distribution strategy of movie studios depends on the substitutability among channels. If channels are strong substitutes for each other, the optimal distribution strategy should be sequential. On the other hand, if channels are weak substitutes, or complements, and consumers can buy from multiple channels, the optimal distribution strategy should be simultaneous release with reduced prices. August, Dao, and Shin (2015) extended the model in Calzada and Valletti (2012) by considering the effect of congestion in theaters on consumers' decisions of moviegoing. Their model assumes that consumers are averse to crowds at theaters, and this aversion moderates the optimal release timing and the durability of the attraction of a movie. Their analysis suggests that studios should release home entertainment products simultaneously with theatrical releases if consumers' aversion to congestion is high, and delay home entertainment release for high-quality movies if consumers' aversion to congestion is low.

Recently, Gilchrist and Sands (2016) show that a shock to theatrical viewership in the opening weekend spills over to the theatrical demands in subsequent weeks of the theatrical window. They use the unexpected temperature change on the opening weekend to instrument for the national theatrical viewership in the opening weekend. They find that the spillover occurs at a local (metropolitan) level, and attribute this local spillover to the presence of network externalities. Even though their paper and our paper focus on different channels—theirs examines within-channel spillover, whereas ours examines cross-channel spillover—both papers exploit the randomness of weather to test for and quantify the spillover effect.

Our research extends the literature in three aspects. First, we find credible empirical evidence of a domino effect (that is, a positive causal relationship) of theatrical viewership on home entertainment demands. Second, our finding of the positive causal effect of theatrical viewership on subsequent home entertainment demands provides a plausible explanation to support the other researchers' finding of an inverted U-shape relationship between studios' channel revenue and the time-to-DVD release. Lastly, our research provides empirical evidence to inform theoretical models such as Calzada and Valletti's, regarding the substitutability between these two important channels for movies.

1.3 Mechanisms

Hennig-Thurau et al. (2007) suggest three dominant mechanisms behind the finding that higher theater attendance causes higher DVD sales:

1. The multiple-purchase effect: a consumer's in-theater consumption of a movie simulates his/her purchase of the DVD. Learning could cause this effect—information on the quality of the movie and taste matching is revealed to a consumer when he watches the movie in the theater, and the revealed information reduces uncertainty. Later, when the consumer contemplates which movie to choose for DVD purchase for his own consumption or collection, he is more likely to purchase the DVDs of the movies with less uncertainty than those about which he has less information.

2. The information-cascading effect: in-theater consumption of a movie increases the likelihood of a consumer spreading word-of-mouth; after watching a movie in the theater, a consumer may tell

others in her local social circle about this movie and raise awareness for the movie in the geographic market. This higher level of awareness in turn leads to stronger sales in the DVD release window.

3. The uninformed-cascading effect: higher posted box office numbers from a more successful theatrical release create higher awareness in the market, and in turn lead to higher demand for the movie's DVD.

To investigate the relative plausibility of these three mechanisms in our setting, we conducted an online survey on the consumer theatrical and DVD purchase histories for movies (see Appendix A for the list of survey questions). Our survey was conducted through Amazon's Mechanical Turk (n=223). We asked respondents to report the number of movies they had seen in theaters and the number of DVDs they had purchased during the last five years. We then inquired about the percentage of DVDs they had purchased after seeing the movie in theaters. In addition, we asked them to provide reasons that they buy the DVDs of movies they have already seen in theaters. These survey questions aim to test for the existence of a multiple-purchase effect. We also asked the respondents the percentage of DVDs they had purchased because of word-of-mouth from friends and the percentage of DVDs they had purchased simply because the movie was a huge box office success. These two survey questions aim to investigate the existence of an information-cascading effect and an uninformed-cascading effect.

Of our 223 respondents, 70% had purchased DVDs in the last five years for movies they had seen in theaters. Eighty percent of these respondents stated that one of the key reasons they purchased DVDs after seeing the movies in theaters was to re-watch it, and 25% of these respondents stated that they purchased the DVD as a gift for friends and family (respondents were allowed to choose multiple reasons). Furthermore, excluding the respondents who purchased few DVDs (one or two DVDs in last five years), we found that 12% of all the purchased DVDs for respondents in our sample were for movies that consumers had seen in theaters. This result is consistent with the existence of the multiple-purchase mechanism, because the survey shows that consumers occasionally buy DVDs of movies they have watched in theaters. On the other hand, 22% and 13% of all the DVD purchases were motivated by word-of-mouth from friends and by awareness generated by the movie's box office success, respectively. These results suggest that informed-cascading and uniformed-cascading effects may also drive the observed positive spillover from the theatrical channel to the DVD retailing channel.

An alternative explanation for the empirical result in our analysis below is that our finding of higher theatrical viewership leading to higher DVD sales is not driven by consumer behaviors, but rather by firms' strategic actions. That is, movie studios and DVD retailers set their DVD pricing and advertising strategies based on box office performance, and these strategic actions based on observed box office performance cause changes in DVD sales. However, this alternative explanation is unlikely to be valid in our setting. This paper uses market-level data to analyze the effect of theatrical viewership on DVD sales, whereas this alternative explanation would suggest that studios and retailers set their DVD marketing-mix variables at a city or regional level as a reaction to the local box office performance. We reached out to two executives at the data-providing movie studios, and they stated that their studios do not set DVD marketing strategy at the local market level in response to theatrical popularity in that city.

1.4 Data

This paper uses DVD/Blu-ray sales and box office data from three major U.S. movie studios. We use each movie's box office gross revenue divided by the national average movie ticket price in the year of release as a proxy for theatrical attendance. The three participating movie studios provided data for movies from different but overlapping release years: 2003–2012, 2006–2013, and 2011–2013.

To maintain relative homogeneity across titles, we focus on wide-release movies—movies that had more than 600 opening theaters in the United States, because platform releases (movies released in a small number of theaters initially) are systematically different than titles released using the (more common) wide-release strategy. We also exclude foreign films that were released internationally several months to a year earlier than in the United States, because these movies are fundamentally different than the U.S.-produced movies and because the higher availability of pirated copies from early international releases might affect the box office and DVD/Blu-ray sales.

The unit of analysis is the sales of a movie in a city. We have a total of 20,723 observations from 103 movies in 204 cities. For each movie-city unit, the dependent variable is the sales[1] of DVDs and Blu-ray discs sold through three big-box retailers (Walmart, Target, and BestBuy). We derive the DVD/Blu-ray sales of a movie by multiplying the unit sold with the national average retail price of the DVD for that movie. Following the work of Eliashberg and Shugan (1997), Basuroy, Chatterjee, and Ravid (2003), and Liu (2006), we use a window of the first eight weeks for the sales of both theatrical and DVD/Blu-ray releases. The box office receipts of blockbuster-type movies decay exponentially over time (Ainslie, Drèze, and Zufryden 2005), and receipts from the first eight weeks of theatrical release on average account for more than 95% of the box office revenue from the entire theatrical release window. We find that the volume of DVDs/Blu-ray discs sold over time follows a similar exponential decay pattern for the first three to four weeks and then stabilizes to a small stream of sales from the fourth week onward. Because the demand in both channels is heavily concentrated in the early weeks, analyses using the first eight weeks of sales are reasonable.

Table 1.1 presents the variable descriptions. In the following section, we discuss each of the explanatory variables in detail.

Explanatory variables at movie-market level

1. ***Theatrical attendance:*** We estimate attendance by dividing the total box office revenue from all theaters in the market for the movie in the first eight-week window by the national average movie ticket price in the year of release. We include city fixed-effects in our models to resolve the issue of variation in ticket prices across cities.

2. ***Snowstorm instruments:*** We use an opening-weekend-snowstorms instrument and a prior-week-snowstorms instrument. The opening-weekend-snowstorms indicator is set to one if any severe winter event occurred in the geographic market during the theatrical opening weekend; the prior-week-snowstorms indicator is set to one if any severe winter event occurred during the seven-day window

[1] As a robustness check, we also analyze the case where the dependent variable is the number of DVD/Blu-rays sold. The result is presented in Section 7. The two set of results are consistent with each other.

before the day of the theatrical opening. A severe winter event is defined as a report of a Blizzard, Heavy Snow, Ice Storm, Winter Storm, or Winter Weather in the Storm Events Database from the National Oceanic and Atmospheric Administration's National Climate Data Center. The records in the Storm Events Database are at the county level. Because a city can comprise multiple counties, we choose the county seat of the city when we merge the county-level weather data with the city-level sales data. The severe-weather-event records are based on reports from various local sources such as the Park or Forest Service, trained spotters, and emergency managers. Because the severe winter events are based on trained personnel in the local area, these snowstorms are adjusted for snowfall in the local area. In other words, four inches of snowfall overnight may trigger a heavy snow event in a warmer-temperature city but may not trigger the same event in a colder-temperature city that is more accustomed to snow.

Explanatory variables at the movie level

3. ***Movie characteristics:*** We collected data on movie characteristics including number of opening screens in the United States, month of theatrical release, studio, genre, MPAA rating, IMDB user-review rating, and production budget. We obtained these data from IMDB and Boxofficemojo websites. We also collected data on the presence of star actors in the movies, using IMDB's STARmeter. The STARmeter is designed to capture the level of public interest in an actor or actress based on the frequency with which his or her profile is viewed on the site. This variable is comparable to the Hollywood Reporter's Star Power Index, which is used by other papers in the literature to control for the presence of star actors (Elberse and Eliashberg 2003; Gopinath, Chintagunta, and Venkataraman 2013).[2] We set the indicator variable for star actors to 1 if any of the movie's cast is in IMDB's STARmeter Top 10 list the year of and the year immediately after theatrical release. We use presence on two consecutive years' lists to determine whether an actor or actress is considered a major star, because lags may exist between the rise of a star and the year the new star appears on the IMDB list. In addition, we obtained advertising

[2] We used the IMDB STARmeter measure in our paper instead of the Hollywood Reporter Star Power Index because the most recent Hollywood Reporter star-power ranking was published in 2006, well before our study period.

expense data from Kantar Media for each movie in our data. We use the month of theatrical release and whether the movie was released during Christmas school holidays (between December 23 and January 2) to control for the timing of movie releases. We also note that movie studios strategically choose the timing of theatrical openings based on revenue expectations. For example, movies with lower commercial expectations are more likely to be released in January than in other winter months. By including calendar month fixed-effects in our model, we control for these release-timing strategic effects, because the model effectively considers only variations across movies within the same calendar month. We also include year fixed-effects to remove the confounding effects of economic cycles and other time trends. Lastly, to control for the magnitude of competition of a movie in a theater, we use the total production budgets of the movies released the same week as the focal movie. This variable is similar to the control of competition for "screen space" from new releases used in Elberse and Eliashberg (2003).

4. ***DVD price at release:*** We control for the price of the DVD at the time of its release because DVD price may be a factor in a consumer's DVD purchase decision. The average price of DVDs in the first week of release is calculated by dividing the national DVD sales volume by the national DVD units sold in the first week of DVD release.

5. ***Number of weeks between theatrical and DVD releases:***

   We control for the length of delay of the DVD release after the release of the movie in theaters by computing the number of weeks in between the theatrical opening date and the DVD release date.

6. ***Characteristics of competing DVDs at the week of DVD release:***

   To control for the magnitude of competition during the DVD release, we use the total production budgets of the new DVDs released the same week as the focal movie.

Table 1.1 Data

Variable	**Measure**	**Source**	**Level of Variation**
DVD volume sold	Total number of DVDs sold for first four weeks of DVD release	movie studios	Movie-city
DVD sales	DVD volume sold multiplied by the national price of DVD	movie studios, The-numbers.com	Movie-city

Box office	Total box office of the first eight-week window from all theaters in the market for the movie	movie studios	Movie-city
Theatrical attendance	Total box office of the first eight-week window from all theaters in the market for the movie divided by the national average movie ticket price in the year of release	Box office: movie studios Average movie ticket price: National Theater Owners Association	Movie-city
Price of DVD at release	U.S. DVD revenue divided by units sold in the week of DVD release	The-numbers.com	Movie
Production budget	Production budget	Internet Movie Database	Movie
Advertising expenditures	Advertising expenditures in U.S.	Kantor	Movie
Number of opening theaters	Number of theaters for opening week	Internet Movie Database	Movie
Movie genre	Movie genre (Action, Comedy, Drama, Family/Animation, Horror)	Internet Movie Database	Movie
Stars cast indicator	Dummy variable indicating whether this movie has any cast in IMDB's STARmeter Top 10 list	Internet Movie Database	Movie
MPAA rating	MPAA rating (G, PG, PG-13, R)	Internet Movie Database	Movie
IMDB user rating	Review rating for the movie based on average votes by IMDB users	Internet Movie Database	Movie
Total budget of competing movies in the first week of theatrical release	Sum of the production budgets of movies that were released in theaters in the same week as the focal movie	Internet Movie Database	Movie
Total budget of competing movies in the first week of DVD release	Sum of the production budgets of movies that were released in DVDs in the same week as the focal movie	Internet Movie Database, The-numbers.com	Movie
Month of theatrical release	The calendar month of the movie opening in theaters	BoxofficeMojo.com	Movie
Time-to-release of DVD	The number of weeks between DVD/Blu-ray release and theatrical open	Internet Movie Database, The-numbers.com	Movie
Occurrence of any snowstorm during the opening weekend of theatrical release	Dummy variable indicating whether a snowstorm occurred in the city at any point during the opening weekend of theatrical release	National Climate Data Center – Storm Event Database	Movie-city
Occurrence of any snowstorm during the 7-day window prior to the theatrical release date	Dummy variable indicating whether a snowstorm occurred in the city during the 7-day window prior to the theatrical release date	National Climate Data Center – Storm Event Database	Movie-city

1.5 Model Specification and Empirical Strategy

We postulate a flexible system of the relationship between theatrical attendance and subsequent DVD/Blu-ray sales for movie *m* in city *d*:

$$\tilde{Y}_{md} = M_d^{DVD}\, Y_{md}^*$$

$$Y_{md}^* = \tilde{g}(X_{md}^*, W_{md}, \varepsilon_{md})$$

$$\tilde{X}_{md} = M_d^{Theater}\, X_{md}^*$$

where the outcome variable $\tilde{Y}_{md}$ denotes the sales of DVDs/Blu-ray discs sold through three major big-box retailers in city *d* for movie *m*; M_d^{DVD} is the potential market size for DVD consumers in city *d*; latent variable Y_{md}^* can be interpreted as the average revenue generated from DVD purchased of movie *m* for a consumer in market *d*. This average revenue from DVD/Blu-ray discs purchased, Y_{md}^*, is an unknown smooth function $\tilde{g}$ of latent variable X_{md}^*, the average theatrical attendance of movie *m* per consumer in city *d*; $W_{md}$is a set of explanatory variables; and ε_{md} is the error term. Although X_{md}^* is not observed, this per-capita theatrical attendance is related to the observed total theatrical attendance of movies in that market and $M_d^{Theater}$, the market size of movie-goers in city *d*. Explanatory variables W_{md} comprise the set of variables discussed in the previous section.

We are interested in estimating the following model for the relationship between theatrical attendance and subsequent DVD/Blu-ray sales, derived by taking the logarithm of the system described above. The log-log specification allows us to interpret the estimated causal effect as elasticity—that is, the percentage change in subsequent DVD/Blu-ray sales in big-box retailers as a result of the percentage change in theatrical attendance.

$$Y_{md} = g(X_{md}, W_{md}, \varepsilon_{md})$$

where

$$Y_{md} = \log \tilde{Y}_{md} - \log M_d^{DVD}$$

$$X_{md} = \log \tilde{X}_{md} - \log M_d^{Theater}$$

and function g is a transformed $\tilde{g}$ and is assumed to be strictly monotonic in the error term ε_{md}. In other words, Y_{md} denotes the log of sales of DVD/Blu-ray discs sold through three major big-box retailers in city d for movie m, and X_{md} denotes the log of movie attendance in city d for movie m. The unknown potential market sizes for DVD/Blu-ray and theatrical consumption, $\log M_d^{DVD}$ and $\log M_d^{Theater}$, are treated as fixed-effects in our model. These city fixed-effects capture between-city differences so that our analysis can focus on the within-city causal effect that has consumer behavioral interpretation.

1.5.1 Empirical Strategy

The identification challenge arises from omitted variables, in spite of the inclusion of city fixed-effects and explanatory variables. Omitted-variable bias could arise from unobserved movie popularity factors that our other explanatory variables do not fully capture. More popular movies are likely to have both higher theatrical viewership and higher DVD/Blu-ray sales, thus confounding the causal effect of theatrical viewership on DVD/Blu-ray sales. Compounding the omitted variable issue, the unobserved popularity factor can differ across cities even for the same movie. For example, films with Christian themes can have broad appeal in cities with a larger proportion of Christians, but may not be so popular in cities with smaller proportion of Christians. And the religious composition of cities varies widely: 48% of adults in the San Francisco metropolitan area and 78% of adults in the Dallas metropolitan area identify as Christians (Pew Research Center, 2014 U.S. Religious Landscape Study). Because unobserved popularity factors can vary by movies and by cities, including movie fixed effects in the model would not resolve the omitted variable bias satisfactorily. Econometrically, the existence of unobserved confounding factors that influence both DVD purchase and theatrical attendance decisions means that X_{md}, the log-transformed theatrical attendance, is not conditionally independent of ε_{md}, the error term in the determinant of DVD/Blu-ray sales. Not addressing this endogeneity issue would lead to a biased estimate of the causal effect of interest.

To overcome these identification challenges, we need a source of plausibly exogenous city-level variation in theatrical attendance that is independent and correlated with these unobserved confounders, conditional on the explanatory variables. The occurrence of a snowstorm during the theatrical opening weekend is an ideal instrument for theatrical attendance, because it affects theatrical attendance without directly affecting the DVD/Blu-ray sales volume. In other words, snowstorms “move” the theatrical attendance in a way that is conditionally independent from the unobserved confounders. We can then disentangle the true effect of higher theatrical viewership on subsequent DVD/Blu-ray demand from the effects of confounders by analyzing the change in subsequent DVD/Blu-ray demand as a result of these exogenous changes in theatrical attendance. We explain in the following paragraphs that snowstorms around theatrical openings are suitable instruments for identifying the effect of theatrical attendance on DVD/Blu-ray demand because (1) snowstorms during theatrical release affect theatrical attendance, (2) the occurrence of snowstorms is random conditional on cities and time of year, (3) major snowstorms can be predicted at most seven days in advance, and, thus, studios cannot reschedule a theatrical opening date to avoid an upcoming snowstorm in a particular city, and (4) these snowstorms do not have any lingering direct effect on the demand for DVDs/Blu-ray discs released four to five months after the theatrical release.

When snowstorms happen during a movie’s opening weekend, theatrical attendance decreases because the snowstorms impede consumers’ travel to theaters and cause some moviegoers to stay home. Moreover, not all of these affected moviegoers see the missed movie in theaters in later weeks. Our data suggest that only about a third of the lost theater attendance is recouped in the weeks subsequent to the opening weekend, and, therefore, a snowstorm during opening weekend has a lasting impact on the eight-week aggregate theatrical viewership. In summary, snowstorms significantly influence theatrical attendance in a market.

On the other hand, when snowstorms hit a city the week before the theatrical opening weekend, theatrical attendance increases. These storms prevented some consumers from going to theaters, but a week later, a portion of these consumers may still have an itch to watch movies, and some of them may switch to watch the newly-released focal movie when they return to theaters.

Snowstorms are random and can only be predicted with a short lead-time. Conditional on the calendar month and the city, the occurrence of snowstorms on any given weekend is random. The formation of a snowstorm is forecasted at most one to two weeks ahead. Movie studios schedule movie releases several months ahead of the actual opening date and thus cannot accurately predict whether a snowstorm will occur during a scheduled theatrical opening. In fact, an article in *The New York Times* (2016) reports that the current weather forecast techonology can only accurately predict the onset of snowstorms seven days ahead of time. The short lead-time exacerbates the logistic challenge in postponing local release dates in response to a forecasted snowstorm. Because of the challenge of last-minute schedule negotiations with cinemas and the cost of additional advertising for any new release date in a particular city, studios do not postpone a movie's release after receiving an accurate forecast of a snowstorm. The randomness and unpredictability of snowstorms and the high cost of last-minute rescheduling of theatrical releases suggest that the coincidence of a snowstorm on a theatrical opening weekend should be conditionally independent from any unobserved confounders conditional on the explanatory variables.

In addition, a snowstorm's effect on the impacted cities is transient. Snowstorms in the United States usually last two to five days. Because DVD/Blu-rays are released four to five months after theater releases, the occurrence of a snowstorm at the time of theatrical opening is highly unlikely to directly affect the sales of the DVD/Blu-ray discs. Any effect of snowstorms on DVD/Blu-ray sales should be attributed to the indirect effect of snowstorms influencing theatrical attendance in the area and, in turn, the change in theatrical attendance affecting the subsequent DVD/Blu-ray sales. The view that snowstorms have a transitory effect on the affected area is supported by Bloesch and Gourio (2015), who analyzed state-level economic time series and concluded that temperature and snowfall shocks have only short-lived economic effects.

1.5.2 Model Specification

Using occurrences of snowstorms as an instrument for theatrical attendance, we expand the aforementioned equations system to the following model

$$Y_{md} = g(X_{md}, W_{md}, \varepsilon_{md})$$

$$X_{md} = h(Z_{md}, W_{md}, \eta_{md})$$

where Y_{md} denotes the log of sales of DVDs/Blu-ray discs sold through three major big-box retailers in city *d* for movie *m;* X_{md} denotes the log of movie attendance in city *d* for movie *m*; Z_{md} is the set of snowstorm instruments; g is an unknown smooth function that is strictly monotonic in the error term ε_{md}; W_{md} is a set of explanatory variables; h is an unknown smooth function that is strictly monotonic in η_{md}, and η_{md} is a scalar error term in the equation of the determinants of theatrical attendance.

Our nonparametric specification is robust against misspecification of functional form and distributional assumptions. Furthermore, our model specification can capture interactions between instruments, covariates, and the error terms. And because the error terms enter each equation through the unknown functions g and h respectively, these error terms are known as nonseparable (Torgovitsky 2015) and capture heterogeneity.

1.5.3 Object of Interest

We are interested in the "average partial effect" (APE) (cf. Blundell and Powell (2003); Wooldridge (2005)) of log theatrical attendance X_{md} on log DVD sales Y_{md}.

$$APE = E\left[\frac{\partial}{\partial x_{md}} Y_{md}(x_{md}, w_{md})\right]$$

The average partial derivative of the dependent variable Y_{md} with respect to the endogenous variable X_{md} can be an important measure of the marginal effect of an exogenous shift in the endogenous variable (Blundell and Powell 2003). The average partial effect is commonly used for the inference of average effect (e.g., Bester and Hansen (2009); Blundell and Powell (2003); Florens, Heckman, Meghir, and Vytlacil, (2008); Imbens and Newey (2009)).

1.5.4 Identification Assumption

We use the control function approach to handle the endogeneity issue and estimate the average partial effect. The key assumption in the control function approach for identification is that there exists an estimable control variate V such that X and ε are independent conditional on V. In other words, a control function C of endogenous variable X and instruments Z is a function such that the control variate $V = C(X, Z)$ leads to conditional independence $X \perp \varepsilon \mid V$. Kasy (2010) showed that the control function approach is valid for a triangular system such as ours, when the function h is strictly monotonic in the error term η and error terms η and ε are both unidimensional. The control function approach has been used in different settings in the marketing literature (Luan and Sudhir 2010; Petrin and Train 2010). Imbens and Newey (2009) showed that $F_{X_{md}|Z_{md},W_{md}}(x_{md}, z_{md}, w_{md})$, the conditional cumulative distribution function of endogenous variable X_{md} given instrument Z_{md} and explanatory variables W_{md}, is a valid control variate for triangular models. Furthermore, they proved that this control variate enables the identification of the average partial effect, as given by

$$APE = E\left[\frac{\partial}{\partial x_{md}} m(x_{md}, v_{md}, w_{md})\right]$$

where $m(x_{md}, v_{md}, w_{md}) = E[Y_{md}|X_{md} = x_{md}, V_{md} = v_{md}, W_{md} = w_{md}]$. That is, the average partial effect can be derived from the conditional mean function of dependent variable Y_{md} given the endogenous variable X_{md}, control variate V_{md}, and explanatory variables W_{md}. Under the assumptions in our model, the average partial effect can be point-identified using continuous, discrete, or even binary instruments (D'Haultfœuille and Février 2015; Torgovitsky 2015)

1.5.5 Estimation Approach

Imbens and Newey (2009) suggested a two-stage approach to estimate the average partial effect.

The control variate $\hat{V}_{md} = \hat{F}_{X_{md}|Z_{md},W_{md}}(x_{md}, z_{md}, w_{md})$ is estimated in the first stage, and then the function $m(x_{md}, v_{md}, w_{md})$ is estimated by using the fitted control variate $\hat{V}$ together with the endogenous variable X_{md} and explanatory variables w_{md} to estimate the conditional mean function $\hat{m}(x_{md}, v_{md}, w_{md})$ in the second stage.

The first stage estimates the control variate, which requires us to estimate the distribution of the endogenous variable X conditional on instruments Z and explanatory variables W. We use the kernel method to nonparametrically estimate this conditional distribution $F_{X|Z,W}$. For simplifying the exposition, our description of the estimating approach will lump the explanatory variables W and instruments Z into a single set of variables Z^*, that is, $Z^* = (Z, W)$. Lumping the two sets of variables happens without loss of generality, because a control function does not differentiate between conditioning on an instrument or an explanatory variable.

We use the estimator proposed by Li and Racine (2008) to estimate the conditional cumulative distribution function (CDF) of X given Z^*,

$$\hat{F}_{X|Z^*=z} = \frac{1}{N}\sum_{j=1}^{N} \Phi\left(\frac{(x - x_j)}{b_1}\right) K_0(z_j, z; b_2) \,/\, \hat{f}(z)$$

where b_1 is a positive scalar bandwidth; $\Phi\left(\frac{x}{b_1}\right)$ is a smooth approximation to the empirical CDF for X; $K_0(\cdot,\cdot\,; b_2)$ is a generalized product kernel with a vector of positive bandwidths b_2; $z_j$is the j-th observation of data; $\hat{f}(z) = \frac{1}{N}\sum_{j=1}^{N} K_0(z_j, z)$, which is the kernel estimator for the density $f(z)$.

To estimate the conditional CDF at any given point z, this kernel estimator effectively computes an average of the smoothed[3] empirical CDF of X using all observations in the original data, weighed by

[3] Even though one can construct a conditional CDF estimator using the *unsmoothed* indicator functions of the dependent variable (X in this case), Yu and Jones (1998) recommend the smoothed approach.

the similarity of each observation to the given point z. The generalized product kernel $K(\cdot,\cdot\,; b_2)$ defines the weights. Because we are conditioning on p variables (p = number of instruments + number of explanatory variables), the product kernel $K(\cdot,\cdot\,; b_2)$ operates on vectors of p-length and the bandwidth vectors are also of p-length. The generalized product kernel is the product of a series of univariate kernels.

$$K_0(z_j, z\,; b_2) = \prod_{l=1}^{p} K_l(z_{j,l}, z_l\,; b_{2,l})$$

where $K_l(\cdot,\cdot\,; b_{2,l})$ is an univariate kernel for the l-th dimension of Z^*, and $b_{2,l}$ is the bandwidth associated with this univariate kernel; $z_{j,l}$ and z_l are the l-th dimension of z_j and z, respectively. We use a second-order Gaussian kernel for a continuous variable and a modified Aitchison-Aitken kernel (Li and Racine 2003) for a categorical variable.

$$K_l(z_{j,l}, z_l\,; b_{2,l}) = \begin{cases} K_l^{(c)}(z_{j,l}, z_l\,; b_{2,l}) & \text{if } z_{j,l}, z_l \text{ are continous} \\ K_l^{(d)}(z_{j,l}, z_l\,; b_{2,l}) & \text{if } z_{j,l}, z_l \text{ are categorical} \end{cases}$$

$$K_l^{(c)}(z_{j,l}, z_l\,; b_{2,l}) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\left(\frac{z_{j,l} - z_l}{b_{2,l}}\right)^2}{2} \right)$$

$$K_l^{(d)}(z_{j,l}, z_l\,; b_{2,l}) = \begin{cases} 1 & \text{if } z_{j,l} = z_l \\ b_{2,l} & \text{otherwise} \end{cases}$$

The choice of bandwidth parameters is crucial in nonparametric methods, whereas the choice of kernel is relatively unimportant (DiNardo and Tobias 2001). We choose the bandwidth parameters using the leave-one-out cross-validation approach in Li, Lin, and Racine (2013). Their approach sidesteps the computational-intensive numerical integration in each iteration of the minimization of the cross-validation objective function. The chosen optimal bandwidth is used to construct the estimator of the conditional CDF. The fitted control variate $\hat{V}_i$ for each observation can then be calculated by applying the constructed conditional CDF estimator to that observation.

The second stage is the estimation of the conditional mean function of the DVD/Blu-ray sales given the fitted control variate and explanatory variables. We use a Nadaraya-Watson regression to nonparametrically estimate $m(D^*)$, the conditional mean function (CDF) of Y given D^*, where $D^* = (X, \hat{V}, W)$

$$m(D^* = d) \equiv E[Y|D^* = d] = \frac{1}{N}\sum_{j=1}^{N} Y_j\, K_1\big(d_j, d; b_3\big) \,/\, \hat{f}(d)$$

where Y_j is the j-th data point of the dependent variable; $K_1(\cdot,\cdot\,; b_3)$ is a generalized product kernel with a vector of positive bandwidths b_3; $d_j$is the j-th observation of data; $\hat{f}(d) = \frac{1}{N}\sum_{j=1}^{N} K_1\big(d_j, d; b_3\big)$, which is the kernel estimator for the density $f(d)$. The generalized product kernel K_1 is the product of a series of univariate kernels, similar to the definition described in the first stage estimation. The bandwidth parameters for the second stage are chosen by the leave-one-out cross-validation procedure discussed in Li and Racine (2003).

The estimator of the average partial effect is constructed from the estimated second-stage conditional mean function and averaged over the data sample. The estimator of average partial effect is given by

$$\widehat{APE} = \frac{1}{N}\sum_{i=1}^{N} \frac{\partial}{\partial x}\widehat{m}\big(X_i, \widehat{V}_i, W_i\big)$$

and we use numerical differentiation to calculate the partial derivative of the fitted conditional mean function $\widehat{m}$ with respect to x. More specifically, we use the symmetric difference quotient by approximating $\frac{\partial}{\partial x}\widehat{m}(X_i, \widehat{V}_i, W_i)$, the partial derivative with respect to x evaluated at the i-th observation by $\frac{\widehat{m}(X_i+\delta,\widehat{V}_i,W_i)-\widehat{m}(X_i-\delta,\widehat{V}_i,W_i)}{2\delta}$ (Serafin and Wnuk 1987) and choosing $\delta = 0.001$. We use bootstrapping to derive an estimate of the standard error and a confidence interval for the estimator of the average partial effect. Our bootstrap procedure derives an estimator of standard errors similar to the two-way cluster robust estimator in Cameron and Miller (2015), in order to handle correlations in observations across cities or across movies.

1.6 Results

1.6.1 The Effect of Snowstorms on Theatrical Attendance

Snowstorms significantly affect theatrical attendance. We run a generalized additive model regression (Hastie and Tibshirani 1990) to analyze the effect of snowstorms on theatrical attendance[4], controlling for DVD release characteristics, theatrical release information, and city fixed-effects. We find a point estimate of -0.092 (standard error = 0.020) on the opening-weekend-snowstorm instrument and 0.048 (standard error = 0.013) on the prior-week-snowstorm instrument. The result is presented in Table 1.2. The coefficients on the snowstorm instruments are significant at the 0.01 level. The coefficient on opening-weekend snowstorms indicates that when a snowstorm hits a city during the theatrical opening weekend of a movie, the eight-week aggregate theatrical attendance for the movie in that city falls by about 9%. And if a city is hit by a snowstorm during the week before the theatrical opening date of a movie, the eight-week aggregate theatrical attendance for that movie in that city rises by about 5%. This evidence that snowstorms have significant impact on theatrical attendance, coupled with prior research that found no long-term economic impact from severe winter events, suggests that we can use snowstorms to separate out the causal effect of theatrical attendance on the DVD/Blu-ray sales volume from confounders.

Table 1.2 Effect of Snowstorms on Theatrical Attendance

	Dependent variable:

[4] Our first-stage estimator models the conditional CDF. Using the estimated conditional CDF to draw inference on the conditional mean is inappropriate, because asymptotically optimal bandwidths for the estimation of conditional CDF are not equal to those for the estimation of the conditional mean.

	log theatrical attendance
Snowstorm occurred during theatrical opening weekend	-0.092*** (0.020)
Snowstorm occurred within 7 days prior to opening date	0.048*** (0.013)
Controls:	Yes
Price of DVD at release	Yes
Number of weeks between theatrical and DVD releases	Yes
Characteristics of competing DVDs at the week of DVD release	Yes
Movie characteristics	Yes
Month of DVD release	Yes
City fixed-effects	Yes
N_{movie}	103
N_{city}	204
N	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

1.6.2 Effect of Theatrical Attendance on DVD/Blu-ray Sales

Table 1.3 shows the estimated average partial effect of log theatrical attendance on log DVD/Blu-ray sales. The dependent variable is the log sales of DVDs/Blu-ray discs sold through three big-box retailers in the first eight weeks after the movie's DVD release in a city. We control for DVD release characteristics, theatrical release information, and city fixed-effects described in the previous section.

Table 1.3 Effect of Theatrical Attendance on DVD/Blu-ray sales (with and without endogeneity correction)

	Dependent variable: log DVD/Blu-ray sales	
	Our model (with endogeneity correction)	Without endogeneity correction
Average Partial Effect estimate:		
log theatrical attendance (s.e.)	0.240*** (0.029)	0.718*** (0.025)
Controls:		
Price of DVD at release	Yes	Yes
Number of weeks between theatrical and DVD releases	Yes	Yes
Characteristics of competing DVDs at the week of DVD release	Yes	Yes
Movie characteristics	Yes	Yes
Month of DVD release	Yes	Yes

City fixed-effects	Yes	Yes
N_{movie}	103	103
N_{city}	204	204
N	20,723	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The estimated average partial effect has a point estimate of 0.240 (standard error = 0.029) on the log theatrical attendance, and the effect is significant at the 0.05 level. This finding indicates that higher theatrical attendance leads to significantly more DVDs/Blu-ray discs sold for the same movie in the same market. The estimated causal effect from our model is significantly different if endogeneity is not adjusted for. Table 1.3 also shows the estimated effect for a nonparametric model that does not control for the control variate, thus not correcting for endogeneity. The endogeneity-unadjusted model yields an estimated effect of 0.718 with standard error of 0.025. The significant difference of the estimated effects from the two models, one with endogeneity correction and one without, suggests that accounting for endogeneity in our settings is necessary. The positive and significant estimated effect of theatrical viewership on DVD/Blu-ray sales suggests that complementary forces, such as multiple-purchase and word-of-mouth effects, outweigh the substitution effect. Said another way, our results show that, on balance, theatrical consumption complements DVD/Blu-ray sales.

Online streaming has grown in popularity. Online streaming was the second largest home entertainment channel, behind DVD/Blu-ray, in 2015. Netflix started offering online streaming service to subscribers with limited movie selections in 2007 and gradually expanded the number of titles available online. We analyze whether the introduction of online streaming affected the channel relationship between theaters and DVD/Blu-ray retails. Table 1.4 shows the estimated average partial effect of log theatrical attendance on log DVD/Blu-ray sales by year. Point estimates of the effect of theatrical attendance on DVD/Blu-ray sales are lower in some of the earlier years (e.g., 0.211 in 2004 and 0.204 in 2006), as compared to the later years in our data sample (e.g., 0.249 in 2010 and 0.252 in 2011). However, the difference in average effects of the 2004-2007 period and the 2008-2013 period is not statistically significant at the 0.05 level. This suggests that the channel relationship between theaters and DVD/Blu-ray retail remained stable from 2004 to 2013, despite the growth of streaming media as an alternative home entertainment product.

Table 1.4 Effect of theatrical attendance on DVD/Blu-ray sales by year

	Dependent variable: log DVD/Blu-ray sales
Average Partial Effect estimate:	
log theatrical attendance (s.e.)	
2004	0.211** (0.107)
2005	0.232** (0.099)
2006	0.204** (0.090)
2007	0.240*** (0.091)
2008	0.242** (0.093)
2009	0.237** (0.089)
2010	0.249** (0.088)
2011	0.252*** (0.085)
2012	0.240** (0.097)
2013	0.272** (0.116)
Controls:	
Price of DVD at release	Yes
Number of weeks between theatrical and DVD releases	Yes
Characteristics of competing DVDs at the week of DVD release	Yes
Movie characteristics	Yes
Month of DVD release	Yes
City fixed-effects	Yes
N_{movie}	103
N_{city}	204
N	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

To gain insights into the consumer behavioral mechanisms behind the channel complementarity, we examine whether the effect of theatrical attendance on DVD/Blu-ray sales differs by movie quality. We separate our samples into five equal-sized categories by IMDB user rating, and Table 1.5 presents the estimated average partial effect of log theatrical attendance on log DVD/Blu-ray sales for each IMDB rating category, controlling for the same set of controls as the main analysis. The complementarity effect estimates are 0.246 (lowest review rating category), 0.245, 0.237, 0.228, and 0.246 (highest review rating category) for the five review rating categories in ascending order. Differences in average effects across review rating categories are not statistically significant at the 0.05 level. This finding of a null result is consistent with that in Gilchrist and Sands (2016) on social spillovers within the theatrical channel. Our result suggests that the mechanisms behind the complementarity may be unrelated to movie quality. It may be that horizontal differentiation (how well the movie matches the personal taste of the consumer) matters more than vertical differentiation (how good the movie is) in a moviegoer's decision about buying the DVD/Blu-ray disc after watching the movie in the theater.

Table 1.5 Effect of theatrical attendance on DVD/Blu-ray sales by movie quality

	Dependent variable: log DVD/Blu-ray sales
Average Partial Effect estimate:	
log theatrical attendance (s.e.)	
IMDB rating < 5.6	0.246*** (0.065)
IMDB rating [5.6, 6)	0.245*** (0.064)
IMDB rating [6, 6.5)	0.237*** (0.065)
IMDB rating [6.5, 7.1)	0.228*** (0.065)
IMDB rating >= 7.1	0.246*** (0.066)
Controls:	
Price of DVD at release	Yes
Number of weeks between theatrical and DVD releases	Yes

Characteristics of competing DVDs at the week of DVD release	Yes
Movie characteristics	Yes
Month of DVD release	Yes
City fixed-effects	Yes
N_{movie}	103
N_{city}	204
N	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 1.6 shows the estimated average partial effect by movie genre. We find that the complementarity is weakest for horror movies and strongest for family-oriented movies. The average effect is 0.144 (standard error = 0.069) for horror movies and 0.286 (standard error = 0.046). A possible explanation is that consumers are less likely to buy the DVD/Blu-ray after watching a horror movie in the theater because 1) the element of surprise is gone after a consumer learns the plot from watching it in the theater, and 2) horror movies are less suitable as gifts as compared to movies in other genres. On the other hand, theatrical consumption has a stronger complementarity on the subsequent DVD/Blu-ray demand for family-oriented movies, possibly because consumers use the theatrical experience to screen for movies their children enjoy and then purchase the DVD/Blu-ray disc for those movies. Furthermore, our finding that the complementarity is weakest in horror movies corroborates with Ahmed and Sinha (2016)'s recommendation of shortest time-to-DVD release for this genre.

Table 1.6 Effect of theatrical attendance on DVD/Blu-ray sales by movie genre

	Dependent variable: log DVD/Blu-ray sales
Average Partial Effect estimate:	
log theatrical attendance (s.e.)	
Horror	0.144** (0.069)
Comedy	0.190*** (0.048)
Drama	0.242*** (0.054)
Action	0.248*** (0.050)
Family	0.286***

	(0.046)
Controls:	
Price of DVD at release	Yes
Number of weeks between theatrical and DVD releases	Yes
Characteristics of competing DVDs at the week of DVD release	Yes
Movie characteristics	Yes
Month of DVD release	Yes
City fixed-effects	Yes
N_{movie}	103
N_{city}	204
N	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

1.6.3 Effect of Theatrical Attendance on iTunes Rental

After finding empirical evidence that the theatrical channel has a significant and positive domino effect on demand in subsequent DVD/Blu-ray channels, this paper investigates whether this effect also exists for other home entertainment channels. We perform similar analyses on the iTunes rental channel. A major difference between DVD/Blu-ray disc retail and iTunes rental is that consumers can watch the purchased DVD/Blu-ray product an unlimited number of times, whereas rented iTunes movies expire 24 hours after first-time consumption.

We obtained from the three movie studios the ZIP code-level rental revenue from the iTunes platform for 62 wide-released movies in 2007-2013. The ZIP code-level data is then aggregated to the city-level. Our analysis finds that the estimated average partial effect has a point estimate of 0.173 (standard error = 0.089) for the log theatrical attendance on the log rental revenue (Table 1.7). The point estimate suggests that the theatrical channel may have a positive effect on iTunes movie rentals. However, because the iTunes dataset has a shorter sampling period than that of the DVD/Blu-ray data, the small sample lacks statistical power to reject the null hypothesis. We observe the estimated point estimate of the degree of complementarity to be lower for the iTunes rental channel than for the DVD/Blu-ray retail channel. While the finding of differing strength of complementarity can be attributed to a number of factors, it is plausible that some of this difference is driven by the fact that purchased DVD/Blu-ray discs can be re-watched unlimitedly and, thus, better suit the multiple-purchasing or collector consumer segment.

Table 1.7 Effect of theatrical attendance on volume of iTunes rental volume

	Dependent variable: log Volume of iTunes Rental Volume
Average Partial Effect estimate:	
log theatrical attendance (s.e.)	0.173* (0.089)
Controls:	
Movie characteristics	Yes
Month of iTunes release	Yes
City fixed-effects	Yes
N_{movie}	62
N_{city}	204
N	12,164

Note: Analysis performed on wide-release movies in the iTunes data. Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

We also find that the degree of complementarity varies across movie genres in the iTunes rental channel (Table 1.8). Consistent with the finding from the DVD/Blu-ray retail channel, we find the estimated effect of log theatrical attendance on log iTunes rental revenue to be lower for horror movies (point estimate of 0.152, standard error = 0.284) and higher for family-oriented movies (point estimate of 0.272, standard error = 0.207).

Table 1.8 Effect of theatrical attendance on iTunes rental volume by movie genre

	Dependent variable: log Volume of iTunes Rental Volume
Average Partial Effect estimate:	
log theatrical attendance (s.e.)	
Horror	0.152 (0.283)
Comedy	0.184 (0.170)
Drama	0.090 (0.217)
Action	0.251 (0.171)
Family	0.272

	(0.207)
Controls:	
Movie characteristics	Yes
Month of iTunes release	Yes
City fixed-effects	Yes
N_{movie}	62
N_{city}	204
N	12,164

Note: Analysis performed on wide-release movies in the iTunes data. Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

1.7 Robustness Checks

1.7.2 DVD/Blu-ray Sales Revenue versus Sales Volume

We repeat our analysis and use the log volume of DVD/Blu-ray discs sold as the dependent variable. Table 1.10 shows the estimate of the effect of log theatrical attendance on log volume of DVD/Blu-ray discs sold. The same set of control variables in the main analysis is used. The estimated average partial effect now has a point estimate of 0.271 (standard error = 0.026) for the log theatrical attendance on DVD/Blu-ray sales volume, as compared to the point estimate of 0.240 (standard error = 0.029) from the main analysis on DVD/Blu-ray sales revenue. In other words, the conclusion from the analysis of sales volume is qualitatively the same as that from the analysis of sales revenue.

Table 1.10 Effect of theatrical attendance on volume of DVD/Blu-ray sold (with and without endogeneity correction)

	Dependent variable: log Volume of DVD/Blu-ray sold	
	Our model (with endogeneity correction)	Without endogeneity correction
Average Partial Effect estimate:		
log theatrical attendance (s.e.)	0.271*** (0.026)	0.703*** (0.023)
Controls:		
Price of DVD at release	Yes	Yes
Number of weeks between theatrical and DVD releases	Yes	Yes
Characteristics of competing DVDs at the week of DVD release	Yes	Yes

Movie characteristics	Yes	Yes
Month of DVD release	Yes	Yes
City fixed-effects	Yes	Yes
N_{movie}	103	103
N_{city}	204	204
N	20,723	20,723

Note: Movie characteristic controls include total budget of competing movies during theatrical opening, advertising spending, production budget, opening theaters, genre, MPAA category, presence of movie star, and IMDB rating. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

1.7.1 Falsification Test

The validity of our empirical approach hinges on the identification assumption for the snowstorm instruments. Part of the assumption is that snowstorms during the opening weekend of a movie's theatrical release do not have any direct effect on the demand for the DVD released four to five months afterward. We conduct a falsification test to gauge whether this identification assumption holds. The intuition behind our falsification test is that the exclusion restriction assumption implies that snowstorm occurrences would have no association with the DVD/Blu-ray sales for movies whose theatrical attendance was unaffected by snowstorms.

Nine movies in our data were released only in New York City and Los Angeles and then expanded to national release three to four weeks later. Because these movies were not shown in cities outside of New York City and Los Angeles for the first three to four weeks of the initial limited release, snowstorm instruments constructed using the initial limited-release date should have no effect on theatrical attendance for cities other than New York City and Los Angeles.

Table 1.9 presents the results of the falsification test. The falsification test regresses log DVD/Blu-ray sales on the snowstorm instruments constructed using the initial limited-release date. The point estimate of the coefficient on the opening-weekend-snowstorm instrument is -0.015 (standard error = 0.033) and the point estimate of the coefficient on the prior-week-snowstorm instrument is 0.012 (standard error = 0.036). These estimates show that snowstorm occurrences that do not affect theatrical attendance do not affect DVD/Blu-ray sales. This finding suggests the absence of a direct effect of snowstorms on DVD/Blu-ray sales, and lends credibility to the identification assumption in our empirical approach.

Table 1.9 Falsification test of IV strategy. Do the instruments affect DVD/Blu-ray sales directly?
Reduced-form result for sample of limited-release
Movies that expanded to national release at least 2 weeks after initial release

Dependent variable: log DVD/Blu-ray sales	
	(1)
	Limited release, exclude-NY, LA sample
Opening-weekend-snowstorm indicator	-0.015 (0.033)
Prior-week-snowstorm indicator	0.012 (0.036)
Year fixed-effects	Yes
City fixed-effects	Yes
N_{Movie}	9
N_{city}	120
N	1080
R^2	0.97

Note: The regression is run on the limited releases that took place from November through March, and then expanded to national wide release at least two weeks after the initial limited release. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

1.8 Discussion

Although there is a well-known correlation between a movie's theatrical revenue and its DVD/Blu-ray revenue, there is no rigorous empirical research analyzing whether increased theatrical sales for a movie are causally related to increased demand in the subsequent DVD/Blu-ray release window. On one hand, an increase in theatrical attendance would substitute for DVD/Blu-ray demand if theatrical experience is relatively undifferentiated from the experience of watching a DVD/Blu-ray at home; on the other hand, an increase in theatrical attendance could boost DVD/Blu-ray demand if the two channels are differentiated and/or complementary forces from the multiple-purchases effect and the social influence effect are large. The direction of the net *causal* effect of the cannibalization versus complementary forces between these two channels has not been answered in the literature. Understanding the causal relationship between these two channels could be particularly important for the motion picture industry given recent reductions in movie release windows,[5] increases in movie ticket prices,[6] and decline in overall theatrical attendance.[7]

Our research addresses this question by using snowstorms as an exogenous shock to the number of people who see a movie in theaters. Our results demonstrate strong empirical evidence that higher theatrical attendance in a market causes higher DVD/Blu-ray sales in the movie's subsequent home entertainment release in the same market. Our analysis of the iTunes rental market yields a similar conclusion. This suggests that theaters have a significant and positive spillover effect on home entertainment demands. Furthermore, we find the degree of complementarity to be weakest for horror movies and strongest for family-oriented movies, and the mechanisms behind the complementarity appear to be unrelated to movie quality. Extrapolating our estimates to the industry environment in 2015, each additional moviegoer brings in about $1.50 extra revenue in DVD/Blu-ray sales, on top of the ticket receipt, to the movie studio. In other words, the spillover effect of theaters on the DVD/Blu-ray channel amounts to about 20% extra revenue on top of the theatrical window.

Although our data do not allow us to identify the mechanism behind the complementarity between these two channels, we conducted a simple online survey that found evidence for each of the mechanisms identified by Hennig-Thureau et al. (2007): the multiple-purchase effect, the informed-cascade effect, and the uninformed-cascade effects. Because we have only aggregate data, this paper identifies only the net effect of cannibalization versus complementary forces. Future research with individual-level panel data augmented with social network records will allow separate identification of these three mechanisms.

Our surprising finding that theaters complement DVD/Blu-ray discs challenges the conventional wisdom in the movie industry. The empirical evidence that higher theatrical viewership causes higher DVD/Blu-ray sales cautions against strategies that encroach on the theatrical channel. Therefore, movie

[5] The National Association of Theater Owners (NATO) reports that the average release window for movies dropped from 5 months and 22 days in 1998 to 3 months and 29 days in 2012 (See Ulin 2013).
[6] *Time Magazine* reports that movie ticket prices hit an all-time high in 2014, averaging $8.17 per ticket (Linshi 2015)
[7] *The Hollywood Reporter* reported that the number of people who saw a movie in the theaters hit a two decade low in 2014 (McClintock 2014).

studios should not drastically expedite the release of home entertainment products, especially for family-oriented movies, because these movies have the strongest channel complementarity among all genres.

1.9 References

Ahmed, S., & Sinha, A. (2016). When It Pays to Wait: Optimizing Release Timing Decisions for Secondary Channels in the Film Industry. *Journal of Marketing*, *80*(4), 20–38. http://doi.org/10.1509/jm.15.0484

Ainslie, A., Drèze, X., & Zufryden, F. (2005). Modeling Movie Life Cycles and Market Share. *Marketing Science*. Retrieved from http://pubsonline.informs.org/doi/abs/10.1287/mksc.1040.0106

August, T., Dao, D., & Shin, H. (2015). Optimal Timing of Sequential Distribution: The Impact of Congestion Externalities and Day-and-Date Strategies. *Marketing Science*, *34*(5), 755–774. http://doi.org/10.1287/mksc.2015.0936

Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(4), 103–117. http://doi.org/10.1509/jmkg.67.4.103.18692

Berry, S., Levinsohn, J., & Pakes, A. (1995). AUTOMOBILE PRICES IN MARKET EQUILIBRIUM. *Econometrica*, *63*(4), 841–890.

Bester, C. A., & Hansen, C. (2009). Identification of Marginal Effects in a Nonparametric Correlated Random Effects Model. *Journal of Business & Economic Statistics*, *27*(2), 235–250. http://doi.org/10.1198/jbes.2009.0017

Bloesch, J., & Gourio, F. (2015). The Effect of Winter Weather on U.S. Economic Activity. *Federal Reserve Bank of Chicago Economic Perspectives*, *39*(First Quarter). Retrieved from https://www.chicagofed.org/~/media/publications/economic-perspectives/2015/1q2015-part1-bloesch-gourio-pdf.pdf

Blundell, R., & Powell, J. L. (2003). Endogeneity in Nonparametric and Semiparametric Regression Models. In M. Dewatripont, L. Hansen, & S. Turnovsky (Eds.), *Advances in Economics and Econometrics* (pp. 312–357). Cambridge: Cambridge University Press.

Boatwright, P., Basuroy, S., & Kamakura, W. (2007). Reviewing the reviewers: The impact of individual film critics on box office performance. *Quantitative Marketing and Economics*. http://doi.org/10.1007/s11129-007-9029-1

Calzada, J., & Valletti, T. M. (2012). Intertemporal Movie Distribution: Versioning When Customers Can Buy Both Versions. *http://dx.doi.org/10.1287/mksc.1120.0716*, *31*(4), 649–667.

Colin Cameron, A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372. http://doi.org/10.3368/jhr.50.2.317

D'Haultfœuille, X., & Février, P. (2015). Identification of Nonseparable Triangular Models With Discrete Instruments. *Econometrica*, *83*(3), 1199–1210. http://doi.org/10.3982/ECTA10038

De Vany, A. S., & Walls, W. D. (2007). Estimating the Effects of Movie Piracy on Box-office Revenue. *Review of Industrial Organization*, *30*(4), 291–301. http://doi.org/10.1007/s11151-007-9141-0

DiNardo, J., & Tobias, J. L. (2001). Nonparametric Density and Regression Estimation. *The Journal of Economic Perspectives*, *15*(4), 11–28. http://doi.org/10.1257/jep.15.4.11

Elberse, A., & Eliashberg, J. (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science*, *22*(3), 329–354. http://doi.org/10.1287/mksc.22.3.329.17740

Eliashberg, J., & Shugan, S. M. (1997). Film critics: Influencers or predictors? *Journal of Marketing*, *61*(2), 68–78.

Florens, J. P., Heckman, J. J., Meghir, C., & Vytlacil, E. (2008). IDENTIFICATION OF TREATMENT EFFECTS USING CONTROL FUNCTIONS IN MODELS WITH CONTINUOUS, ENDOGENOUS TREATMENT AND HETEROGENEOUS EFFECTS. *Econometrica*, *76*(5), 1191–1206.

Gilchrist, D. S., & Sands, E. G. (2016). Something to Talk About: Social Spillovers in Movie Consumption. *Journal of Political Economy*, *124*(5), 1339–1382. http://doi.org/10.1086/688177

Gopinath, S., Chintagunta, P. K., & Venkataraman, S. (2013). Blogs, Advertising, and Local-Market Movie Box Office Performance. *Management Science*, *59*(12), 2635–2654. http://doi.org/10.1287/mnsc.2013.1732

Hastie, T. J., & Tibshirani, R. J. (1990). *Generalized Additive Models*. CRC Press. Retrieved from https://books.google.com/books?id=qa29r1Ze1coC&pgis=1

Hennig-Thurau, T., Henning, V., Sattler, H., Eggers, F., & Houston, M. B. (2007). The Last Picture Show? Timing and Order of Movie Distribution Channels. *Journal of Marketing*, *71*(4), 63–83. http://doi.org/10.1509/jmkg.71.4.63

Imbens, G. W., & Newey, W. K. (2009). Identification and Estimation of Triangular Simultaneous Equations Models Without Additivity. *Econometrica*, *77*(5), 1481–1512. http://doi.org/10.3982/ECTA7108

Jiang, R., Manchanda, P., & Rossi, P. E. (2009). Bayesian analysis of random coefficient logit models using aggregate data. *Journal of Econometrics*, *149*(2), 136–148. http://doi.org/10.1016/j.jeconom.2008.12.010

Kasy, M. (2010). IDENTIFICATION IN TRIANGULAR SYSTEMS USING CONTROL FUNCTIONS. *Econometric Theory*, *27*(03), 663–671. http://doi.org/10.1017/S0266466610000460

Lehmann, D. R., & Weinberg, C. B. (2000). Sales Through Sequential Distribution Channels: An Application to Movies and Videos. *Journal of Marketing*, *64*(3), 18–33. http://doi.org/10.1509/jmkg.64.3.18.18026

Li, Q., Lin, J., & Racine, J. S. (2013). Optimal Bandwidth Selection for Nonparametric Conditional Distribution and Quantile Functions. *Journal of Business & Economic Statistics*, *31*(1), 57–65. http://doi.org/10.1080/07350015.2012.738955

Li, Q., & Racine, J. (2003). Nonparametric estimation of distributions with categorical and continuous data. *Journal of Multivariate Analysis*, *86*(2), 266 – 292.

Li, Q., & Racine, J. S. (2008). Nonparametric estimation of conditional CDF and quantile functions with mixed categorical and continuous data. *Journal of Business & Economic Statistics*, *26*(4), 423–434.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, *70*(3), 74–89. http://doi.org/10.1509/jmkg.70.3.74

Luan, Y. J., & Sudhir, K. (2010). Forecasting Marketing-Mix Responsiveness for New Products. *Journal of Marketing Research*, *47*(3), 444–457. http://doi.org/10.1509/jmkr.47.3.444

Ma, L., Montgomery, A. L., Singh, P. V., & Smith, M. D. (2014). An Empirical Analysis of the Impact of Pre-Release Movie Piracy on Box Office Revenue. *Information Systems Research*, *25*(3), 590–603. http://doi.org/10.1287/isre.2014.0530

Mukherjee, A., & Kadiyali, V. (2011). Modeling Multichannel Home Video Demand in the U.S. Motion Picture Industry. *Journal of Marketing Research*, *48*(6), 985–995. http://doi.org/10.1509/jmr.07.0359

Neelamegham, R., & Chintagunta, P. (1999). A Bayesian Model to Forecast New Product Performance in Domestic and International Markets. *Marketing Science*, *18*(2), 115–136. http://doi.org/10.1287/mksc.18.2.115

Petrin, A., & Train, K. (2010). A Control Function Approach to Endogeneity in Consumer Choice Models. *Journal of Marketing Research*, *47*(1), 3–13. http://doi.org/10.1509/jmkr.47.1.3

Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing Bias in Observational Studies Using Subclassification on the Propensity Score. *Journal of the American Statistical Association*, *79*(387), 516–525.

Sawhney, M. S., & Eliashberg, J. (1996). A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures. *Marketing Science*, *15*(2), 113–131. http://doi.org/10.1287/mksc.15.2.113

Schwirtz, M. (2016, January 23). Winter Storm Aftermath: Live Updates. *The New York Times*. Retrieved from http://www.nytimes.com/live/winter-storm-jonas/meteorologists-pleased-with-accuracy-of-forecasts/

Serafin, R. A., & Wnuk, E. (1987). On the symmetric difference quotient and its application to the correction of orbits (II). A numerical analysis. *Celestial Mechanics*, *42*(1-4), 175–186. http://doi.org/10.1007/BF01232955

Shah, D., Kumar, V., & Zhao, Y. (2015). Diagnosing Brand Performance: Accounting for the Dynamic Impact of Product Availability with Aggregate Data. *Journal of Marketing Research*, *52*(2), 147–165. http://doi.org/10.1509/jmr.13.0530

Torgovitsky, A. (2015). Identification of Nonseparable Models Using Instruments With Small Support. *Econometrica*, *83*(3), 1185–1197. http://doi.org/10.3982/ECTA9984

Walls, W. D. (2008). Cross-country analysis of movie piracy. *Applied Economics*, *40*(5), 625–632. http://doi.org/10.1080/13504850600707337

Wooldridge, J. M. (2005). Unobserved Heterogeneity and Estimation of Average Partial Effects. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 27–55). Cambridge: Cambridge University Press. http://doi.org/10.1017/CBO9780511614491

Yu, K., & Jones, M. C. (1998). Local Linear Quantile Regression. *Journal of the American Statistical Association*, *93*(441), 228–237. http://doi.org/10.1080/01621459.1998.10474104

1.10 Appendix

Survey Questions

1. How many (approximately) movies did you see in movie theaters in the last 5 years?
2. How many (approximately) movie DVDs did you purchase in the last 5 years?
3. In the last 5 years, for what percentage of all the movies you have seen in a movie theater did you later also purchase the DVD?
4. What are your main reasons for buying the DVDs after you saw the movies in theater?
    - ✓ To re-watch the movie
    - ✓ Gifts for friends and family
    - ✓ For your collection
    - ✓ Other reasons
    - ✓ I never bought those DVDs
5. Of the DVDs you have purchased in the last 5 years, what percentage of those did you buy because you did not see the movie in theaters, but heard from friends or acquaintances the movie was good?
6. Of the DVDs you have purchased in the last 5 years, what percentage of those did you buy because you did not see the movie in theaters, but the movie was a huge box office success?

Chapter 2

Chapter 2: Estimation of the Effect of Piracy on Worldwide Theatrical Demands and the Implication on International Release Scheduling

International markets have become a significant contributor to Hollywood movie revenue in recent years. Widespread adoption of new projection technology has enabled movie studios to be flexible in setting their international movie release schedules. However, decisions about the timing of international releases are complicated by piracy. For example, releasing a movie earlier in Russia might boost box office revenue from Russia, but on the other hand it might quicken the timing of a pirated copy originating from Russia, because pirates can tape the released movie in theaters. In turn, as pirated videos can be distributed online and consumed worldwide, the potential increase in piracy due to early release in Russia might cannibalize the box office demands in other countries. In order to properly account for the effect of global cannibalization across geographic markets from piracy on the scheduling of global releases, I estimate both the timing and prevalence of piracy supply by country and the varying degrees of substitution from theatrical demand to pirated videos in different languages for seven major countries.

2.1 Introduction

Releasing a movie in the US weeks before releasing in international markets used to be a longstanding practice of Hollywood movies. This lag was partly due to a technological factor—many theaters in international markets relied on shipments of physical movie reels from the US. Since the second half of the last decade from 2000 to 2010, theaters in international markets have gradually shifted towards digital distribution systems. This technological change allowed global movie release schedules to be more flexible for movie studios, as coordinating a simultaneous release in domestic and international markets became logistically easier. In fact, the number of Hollywood movies released simultaneously in domestic and international markets has increased significantly in recent years.

The decision of international release timing is complicated by piracy. Because pirated videos are distributed online, pirated copies originating in one country can be downloaded by consumers in all other countries. Therefore, piracy in one market not only cannibalizes the theatrical demand in the same market, but also might affect the theatrical demand worldwide. A primary source of piracy during the theatrical window in a geographic market is camcording, the practice of illegally videotaping movies in theaters. It is not uncommon for camcorder copies originating from one country to be made available online several days after the movie opens in theaters of that country. Therefore, the theatrical opening date in one country changes the timing of the piracy supply originating from that country, and in turn indirectly impacts the box office in other markets, through the global channel of piracy.

In order to optimize international release timing, studios need to be informed about the effect of global cannibalization across geographic market from piracy. Private information held by studios and private information held by piracy suppliers may be correlated. This correlation can lead to underestimated cannibalization effect. To address this issue, I estimate jointly the demand of movie, timing and prevalence of piracy supply, and the release schedules by countries.

2.2 Literature

Prior Work on the Methodology of Box Office Estimation

Analysis of the effect of piracy on the box office involves estimating box office revenue—and the estimation of box office revenue has a long history in the literature. Sawhney and Eliashberg (1996) and Ainslie, Drèze, and Zufryden (2005) apply variants of a general gamma model to model box office revenues. Other studies, such as Elberse and Eliashberg (2003) and Luan and Sudhir (2010), regress the log box office revenue on movie characteristics and use instruments to handle endogeneity issues. Boatwright, Basuroy, and Kamakura (2007) estimate a new product diffusion model with product clusters to examine the heterogeneous effects of individual movie critics on box office revenue.

Ainslie et. al. (2005) found that coefficients in the box office model change significantly after accounting for the competition. Not accounting for the effect of other movies in concurrent release is equivalent to positing an unrealistic assumption that other movies in concurrent release are not substitutes for the focal movie. In light of the finding above, our paper accounts for competition and assumes that the competitors to the focal movie are concurrent theatrical showings of other movies and available pirated copies of the focal movie.

Prior Work on the Effect of Piracy on the Box Office

Ma, Montgomery, Singh, and Smith (2014) is the most closely related paper in the literature, in the context of the estimation of the effect of movie piracy on the box office during a theatrical window. These researchers analyzed U.S. box office data and found that the box office revenue of a movie is 19% lower if a pirated copy of the movie is available before the theatrical release. The key differences between our paper and Ma et al. (2014) are 1) we investigate the differential impact of the national origination of piracy on the box office of each major country, whereas Ma et al. (2014) concerns the effect on the U.S. box office regardless of the piracy's country of origin; 2) the estimated effect of piracy in Ma et al. (2014) may be underestimated if piracy producers selectively choose which movies to pirate based on private demand signal. The main analysis of Ma et al. (2014) treats the availability of piracy as exogenous, and their robust check uses propensity score matching, which assumes no unmeasured confounders (Rosenbaum & Rubin, 1984). In contrast, this paper address this issue through jointly modeling the piracy availability and the movie demand, and allows error terms to be correlated in the two systems; 3) this paper accounts for the competitors' effect on the demand of a movie in the theatrical window, whereas Ma et al. (2014) does not.

De Vany and Walls (2007) is another paper that estimates the effect of movie piracy on the box office. Similar to the improvements of this paper on Ma et al. (2014), this paper improves on De Vany and Walls (2007), in that we investigate the differential impact of the national origination of piracy on the box office of each major country, we address the endogeneity issues of piracy supply in the box office equation, and we account for the effect of competition on theatrical demand.

Prior Work on the International Variation of Piracy Rate of Movies

Walls (2008) performed a cross-sectional analysis of the piracy rate of movies across 26 countries. He found that the piracy rate tends to be higher in countries with higher internet usage and in countries with a higher cost of intellectual property right enforcement. He found no empirical evidence of a correlation between piracy rate and per-capita income after controlling for other factors.

2.3 Data

I gathered the weekly box office gross revenue from BoxOfficeMojo.com. In this analysis, I focus on four large markets (US, Mexico, Germany, and Russia). The data periods are from the first week of 2006 to the last week of 2013, thus consisting of 418 weeks. My analysis limits to the set of movies that were wide-released in the US, as these movies are much more likely to also be released internationally and to have high financial potential for release-schedule optimization. My dataset covers 1236 movies within the analysis period. The release dates in each market also come from BoxOfficeMojo.com. And from these release dates, I calculate the release lead/lag in each country relative to that in the US. I also gathered movie characteristics, including production budget, genre, and MPAA rating from the International Movie Database (IMDB).

The camcorder piracy data are obtained from the MPAA. These data indicate all camcorder piracy known to MPAA. The data trace each pirated copy to the theater and country of piracy origin, and contain the language of the pirated copy and the date this pirated copy was available online. With this information, I construct the language-specific availability indicator of piracy for each movie and the time-to-first-available of piracy for each movie in each country.

This paper is methodologically similar to the work of Shah, Kumar, and Zhao (2015). Shah et. al. (2015) address the potential bias in estimating consumers' brand preferences from an aggregate demand model when the store-level product availability information is missing. Shah et al. propose a model in which retailers' probability of stocking a product is estimated from aggregate data and consumers' product choices would depend on the assortment of products available. More specifically, Shah et al. use a multivariate probit model to model the retailers' choices of product assortment, and a random-coefficient logit model over the available product assortment to model the product demand. Common shocks in the assortment model, demand model, and the price equation are allowed to be correlated. A major difference between our paper and that of Shah et. al. (2015) is that our product (piracy) availability is modeled through survival analysis. This difference is because our data are in a panel data-like setting, where we observe the box office and the piracy availability by week over the theatrical window of each movie. As one can envision, the camcorder-pirated copy will eventually be made available, starting from the moment of theatrical release; our modeling of the timing of piracy being made available is a natural way to specify a model of the availability of piracy at any point in time.

My demand model is a random-coefficient logit model of demand (Berry, Levinsohn, & Pakes, 1995). Similar to the specification in Shah, Kumar, and Zhao (2015), we allow common demand shocks to be correlated with the shocks in the piracy availability model. And we follow the approach of Jiang, Manchanda, and Rossi (2009) to estimate the joint system from a Bayesian framework.

2.4 Model Specification

This paper is methodologically similar to the work of Shah, Kumar, and Zhao (2015). Shah et. al. (2015) address the potential bias in estimating consumers' brand preferences from an aggregate demand model when the store-level product availability information is missing. Shah et al. propose a model in which retailers' probability of stocking a product is estimated from aggregate data and consumers' product choices would depend on the assortment of products available. More specifically, Shah et al. use a multivariate probit model to model the retailers' choices of product assortment, and a random-coefficient logit model over the available product assortment to model the product demand. Common shocks in the assortment model, demand model, and the price equation are allowed to be correlated. A major difference between our paper and that of Shah et. al. (2015) is that our product (piracy) availability is modeled through survival analysis. This difference is because our data are in a panel data-like setting, where we observe the box office and the piracy availability by week over the theatrical window of each movie. As one can envision, the camcorder-pirated copy will eventually be made available, starting from the moment of theatrical release; our modeling of the timing of piracy being made available is a natural way to specify a model of the availability of piracy at any point in time.

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2.4.1 Assumptions

I model the weekly box office of a movie in a country as aggregate demand from individual consumption choices. The choice decision process of consumers is that, in any given week, a consumer in the focal country may choose to watch any movie in release in theaters in that country. The consumer watches at most one movie per week. This simplifying assumption of choosing no more than one option is reasonable, because only a very small minority of consumers watch multiple movies in theaters within a week. The consumer watches the movie either in the theater or through piracy (if available at the time). Note that this assumption means that the pirated copy of a movie no longer showing in theaters will not be in the consideration set of consumers. Because movies are perishable goods—the attraction of a movie decays through time—the assumption that the pirated copy of a movie no longer showing in theaters is a negligible substitute for movies fresh in the lifecycle is not unreasonable. Furthermore, the consumer does not watch both theatrical and pirated versions. I make the same simplifying assumption from Moretti (2011), that the consumer may watch the same movie again in a later week. This assumption allows my model to treat the population as independent across each week, without keeping track of the path dependence of consumers' decisions over time. The last assumption is that consumers are myopic, which rules out strategic forward-looking behaviors—e.g., consumers forgo watching a movie this week to save time or money for a more attractive movie that will be released a week later. Without consumer-level data, I cannot identify these strategic forward-looking behaviors.

2.4.2 Consumer Choices and Utilities

At any given week t, a consumer i in the focal country c may choose to watch any movie j from the set of movies showing in theaters in that country. Some of these movies have a pirated copy available online. Consumers may choose to watch a movie's pirated copy or watch the movie in theaters. Consumers may choose to not watch any movie at all.

The utility derived by consumer *i* (in country *c*) for watching movie *j* in theater during time period *t* is specified as

$$U_{ijct}^{(b)} = V_{ijct} + \xi_{jct}^{(b)} + \varepsilon_{ijct}^{(b)}$$

$$V_{ijct} = \kappa_{ic} Week_{jct} + \gamma_{ic}\, Lag_{jc} + X_{jct}\, \beta_{ic}$$

the utility derived for watching the *l*-language pirated copy of movie *j* is

$$U_{ijct,l}^{(p)} = \delta_{ic}\, \alpha_{icl}\, V_{ijct} + \varepsilon_{ijctl}^{(p)}$$

and the utility of outside option is

$$U_{ict}^{(0)} = Month_t\, \tau_{ic} + \varepsilon_{ict}^{0}$$

The utility of watching the movie in the theater consists of a deterministic component V_{ijct} and a stochastic component of both $\xi_{jct}^{(b)}$, the unobserved common demand shock that influences all consumers, and $\varepsilon_{ijct}^{(b)}$, the idiosyncratic consumer shock, and is assumed to be i.i.d. extreme value distributed. Within V_{ijct}, the deterministic component of utility, $Week_{jct}$ represents the number of weeks in release of movie *j* in country *c* in time period *t* (i.e. $Week_{jct} = 1$ during the theatrical opening week in that country); κ_{ic} corresponds to the consumer-specific sensitivity to the freshness of the movie and is conceptually similar to the rate of decay in attractiveness over time in Ainslie et. al. (2005) and Ma et. al. (2014); γ_{ic} measures the sensitivity of the attraction power to Lag_{jc} the delay in the theatrical opening of movie j in country c with respect to other major countries (we operationalize the lead/lag variable as the difference in week between theatrical release in country c and theatrical release in the US); X_{jct} contains the movie characteristics (e.g., genre, production budget, stars) for movie j and time-varying covariates of the movie *j* in country *c* (e.g., number of theaters showing this movie during week *t*); β_{ic} are the consumer-specific sensitivities of the attraction power to these covariates.

The deterministic component of the utility of pirated copy is specified to be the deterministic component of in-theater consumption of the movie multiplied by ratio parameters $\delta_{ic}$and α_{icl}. The ratio parameter δ_{ic} corresponds to the consumer's preference for watching any movie in the theater instead of through piracy, because not all consumers consider piracy as a valid alternative to theatrical release, and some consumers may prefer pirated videos over theatrical consumption. The ratio parameter α_{icl} is language-country-specific and essentially captures a consumer's preference for pirated videos in a different language. The utility of the pirated copy also consists of $\varepsilon_{ijctl}^{(p)}$, an idiosyncratic consumer shock.

Lastly, a consumer may choose to not watch any movie during week *t*. The utility of the outside option in country *c* during time period *t* is ε_{ict}^{0}, plus a monthly seasonal component $Month_t$ with associated coefficients τ_{ic}.

I assume that consumer-specific parameters are invariant over time. Consumer-country-specific parameters are hierarchical specified, with the preference parameters of each consumer within a country drawn independently from the same distribution with a country-specific mean vector. This captures the unobserved heterogeneity of consumer preferences.

$$\begin{bmatrix} \kappa_{ic} \\ \gamma_{ic} \\ \beta_{ic} \\ \delta_{ic} \\ \alpha_{icl_1} \\ \vdots \\ \alpha_{icl_L} \\ \tau_{ic} \end{bmatrix} \sim N\left(\begin{bmatrix} \kappa_{c} \\ \gamma_{c} \\ \beta_{c} \\ \delta_{c} \\ \alpha_{cl_1} \\ \vdots \\ \alpha_{cl_L} \\ \tau_{c} \end{bmatrix}, \Sigma_{\theta\, ic} \right)$$

$$\begin{bmatrix} \kappa_{c} \\ \gamma_{c} \\ \beta_{c} \\ \delta_{c} \\ \alpha_{cl_1} \\ \vdots \\ \alpha_{cl_L} \\ \tau_{c} \end{bmatrix} \sim N\left(\mathbf{0}, \Sigma_{\theta_c}\right)$$

Given the demand system specified above, the market share for the theatrical version of movie *j* in country *c* at time period *t* is

$$s_{jct}^{(b)} = \int \frac{B_{jct} \exp\left(V_{ijct}+\xi_{jct}^{(b)}\right)}{\exp(Month_t\, \tau_{ic})+\sum_{j'} B_{j'ct}\left(\exp\left(V_{ij'ct}+\xi_{j'ct}^{(b)}\right)+\sum_l A_{j'tl} \exp\left(\delta_{ic}\, \alpha_{icl}\, V_{ij'ct}\right)\right)} dF\left(\boldsymbol{\theta}_{ic} \middle| \overline{\boldsymbol{\theta}}, \Sigma_{\theta_{ic}}, \Sigma_{\theta_c}\right),$$

where the binary indicator A_{jtl} represents whether the *l*-language pirated copy of movie *j* is available at time period *t*, and the binary indicator B_{jct} represents whether movie *j* is in theatrical window in country *c* during time period *t*.

Note that in my application, I do not have the data of the number of downloads for pirated movies. The data availability constraint that means that the market share of pirated copies is not observed. Despite the data limitation, our model can still link the variation in piracy availability to the theatrical demands, because variations in the availability and utility of a pirated copy still affect the market shares of the theatrical viewing of movies. One can think of these pirated versions as explicitly modelled outside options.

2.4.3 Availability of Piracy

A pirated copy of a movie is difficult to scrub from online distribution after the initial pirated copy is distributed online, due to the nature of peer-to-peer file-sharing. Therefore, modeling whether a pirated copy of a movie is available in a given week is effectively equivalent to modeling whether a pirated copy has been available during or prior to the week in question.

First, we can create a mapping between the language of the audio track of the pirated copy and the country of piracy origination. The language-week-specific indicator of piracy availability A_{jtl} is equal to 1 if movie *j*'s pirated copy originating from country *c* is available online during week *t*, and 0 if it is unavailable online. This indicator language-week-specific indicator of piracy availability A_{jtl} can be mapped to the country-week-specific piracy availability indicator$\dot{A}_{jt,c}$, through defining a mapping from country of origin to the language of audio track (e.g., US → English or Russia → Russian.) Second, we can then relate the country-week-specific indicator of piracy availability $\dot{A}_{jt,c}$ to the first arrival time of the pirated copy originating from country c, $\mathrm{T}_{j,c}$ using the relationship $\dot{A}_{jt,c} = 1$ if $t \geq \mathrm{T}_{j,\tilde{c}}$ and $\dot{A}_{jt,c} = 0$ if $t < \mathrm{T}_{j,c}$.

Lastly, I specify $\mathrm{T}_{j,c}$, the first arrival time of the pirated copy original from country c, as an accelerated failure time model.

$$\mathrm{T}_{j,c} = \left(e^{M_j\,\phi_c + \omega_c\,Lag_{jc}}\right)\xi_{jc}^{(A)}$$

where M_j is the set of movie characteristics covariates, ϕ_c are the sensitivities to these movie characteristics for country c, Lag_{jc} is the gap in number of weeks between theatrical releases in country c and in the US, ω_c is the sensitivity to the theatrical release gap for country c, and $\xi_{jc}^{(A)}$ is the error term for the determinant of first arrival time of piracy.

2.4.4 Timing of International Theatrical Release

A number of factors, including the widespread adoption of digital projection in international markets, have reduced the gap in the number of weeks between theatrical releases in international markets and the US within the time period of my data. Therefore, I use the calendar year of movie release, which relates to whether the focal movie was released pre or post digital projection, in modeling the international release timing.

$$Lag_{jc} = M_j\psi_c + Year_j\,\gamma_c + +\xi_{jc}^{(L)}$$

where M_j are movie characteristics such as production budget and genre, ψ_C are the associated sensitivities for country c, $Year_j$ is the set of dummies that corresponds to the release year of the movie j, γ_c is the associated parameters for release year in country c, and $\xi_{jc}^{(L)}$ represents the error terms in the equation of international theatrical release timing.

2.4.5 Correlated Common Shocks

The availability of pirated copies and the international release timing might be endogenous in the demand equation. In the market share equations, the availabilities of pirated versions A_{jtl} are endogenously determined by piracy producers. Piracy availability is endogenous because producers of piracy may prioritize the production of pirated movies that are more attractive, and the piracy producers may have a private signal to the demand shock of the reception of a movie in the local market. To deal with the issue of the endogeneity of availability of pirated copies and international release timing, I jointly model the demand side common shock, the stochastic shock to the timing of piracy availability, and the stochastic shock to the international release timing (Jiang et al., 2009).

I assume that that the common demand shocks $\xi_{jct}^{(b)}$ have two components $\mu_{jc}^{(b)}$ and $\omega_{jct}^{(b)}$

$$\xi_{jct}^{(b)} = \mu_{jc}^{(b)} + \omega_{jct}^{(b)}$$

$$\omega_{jct}^{(b)} \sim N(0, \sigma_{\omega}^{2})$$

where $\mu_{jc}^{(b)}$ are movie-country-specific demand side common shocks, and correspond to unobserved common taste shock for a particular movie in a country. Each of these $\mu_{jc}^{(b)}$ common shocks are invariant over the theatrical lifecycle of the movie; $\omega_{jct}^{(b)}$ are movie-country-week idiosyncratic common shocks, and capture variation in unobserved demand factors that affect the attractiveness of the movie to all consumers in a country in a given week.

Then, I tie together $\mu_{jc}^{(b)}$, the movie-country-specific demand side common shock, $\xi_{j,c}^{(A)}$, the error terms in the time-to-piracy equation, and $\xi_{j,c}^{(T)}$, the error terms in the equation of international release timing. I specify these stochastic shocks to be jointly Normal with zero means and covariance matrix Ω:

$$\left(\mu_{jc}^{(b)}, \xi_{jc}^{(A)}, \xi_{jc}^{(T)}\right)' \sim N(0, \Omega)$$

2.5 Estimation

2.5.1 Model Simplification

In the current analysis, I made several simplifications to the model, due to identification and computational issues.

First, I simplified the utility of *l*-language piracy in country *c*. Instead of estimating the full sets of parameters that correspond to all permutations of focal country and language of pirated video, I specify two parameters, one for the national language and one for all other languages. In other words, I replace the utility derived for watching the *l*-language pirated copy of movie *j* in the original specification

$$U_{ijct,l}^{(p)} = \delta_{ic}\, \alpha_{icl}\, V_{ijct} + \varepsilon_{ijctl}^{(p)}$$

by

$$U_{ijct,l}^{(p)} = \begin{cases} \delta_{ic}\, \alpha_{ic0}\, V_{ijct} + \varepsilon_{ijctl}^{(p)} & \text{, if } l \text{ is the national language of country } c \\ \delta_{ic}\, \alpha_{ic1}\, V_{ijct} + \varepsilon_{ijctl}^{(p)} & \text{, if } l \text{ is not the national language of country } c \end{cases}$$

This simplification is driven by the fact that the movies were often released in many international markets in the same week; therefore, it was challenging to identify all l x c language-country parameters.

The second simplification in the current analysis is that I assume the three errors in the demand equation, the time-to-piracy equation, and the international release timing equations to be independent. This simplification is made because of a certain MCMC computational issue that remains to be resolved. Because the correlated errors of the three equations are made to resolve the endogeneity issue, the result of the current analysis may be suspect to endogeneity.

The third simplification is that I am currently using a diagonal covariance to represent consumer preference heterogeneity in the random-coefficient logit demand model. In other words, $\Sigma_{\theta_{ic}}$, the covariance matrix of the individual parameters is a diagonal matrix, instead of a full-blown positive definite matrix.

$$\begin{bmatrix} \kappa_{ic} \\ \gamma_{ic} \\ \beta_{ic} \\ \delta_{ic} \\ \alpha_{icl_1} \\ \vdots \\ \alpha_{icl_L} \\ \tau_{ic} \end{bmatrix} \sim N\left(\begin{bmatrix} \kappa_{c} \\ \gamma_{c} \\ \beta_{c} \\ \delta_{c} \\ \alpha_{cl_1} \\ \vdots \\ \alpha_{cl_L} \\ \tau_{c} \end{bmatrix}, \Sigma_{\theta_{ic}} \right)$$

The reason I made this simplification is that I experienced numerical issues when I used full-blown covariance matrix. Previous studies, such as Jiang et al. (2009), used a small number of draws (e.g., 20-50) to approximate the integral over consumer heterogeneity. My model has many more parameters than the models in previous studies, and my simulation indicated a very large number of draws for my 26-dimensional model. The number of draws increases even further if there is a strong correlation among the 26 parameters. As a result, I made the diagonal-covariance matrix assumption to maintain computational tractability.

2.5.2 Likelihood

The likelihood of the joint model of the theatrical demand (market share) **S**, piracy availability **A**, and international release timing **Lag** is

$$L(\mathbf{\Theta}; \mathbf{S}, \mathbf{A}, \mathbf{Lag}) = \prod_{c} f(G^{-1}(S_c|\mathbf{\Theta}), A_c, Lag_c|\mathbf{\Theta}) \left| J_{\left(\xi_c^{(b)}, \xi_c^{(A)}, \xi_c^{(T)}\right) \to (S_c, A_c, Lag_c)} \right|$$

where G is the linkage function that maps demand-side common shocks to market shares, f is the joint distribution of demand-side common shocks, stochastic shock to first arrival time of the available pirated copy, and stochastic shock to international release lag. J is the Jacobian for transformation from the stochastic shocks to market share, piracy availability, and release timing.

Demand-side common shocks are unobserved, and I need to "invert" the market shares to arrive at the unobserved common shocks. The insight from Berry et al. (1995) is that there is one-to-one mapping between the market shares and unobserved common shocks. Therefore, I use the Anderson acceleration algorithm to back out the unobserved demand-side common shocks from market shares. Evaluation of the linkage function involves integrating over the heterogeneity of consumers within a country, and the integral is approximated by simulation using random draws.

Besides inversion of the market shares, the evaluation of likelihood requires computing the determinant of Jacobians. I use two facts to simplify the evaluation of the determinant of the Jacobian $\left|J_{\left(\xi_c^{(b)},\xi_c^{(A)},\xi_c^{(T)}\right)\to(S_c,A_c,Lag_c)}\right|$. First, I make use of the fact that $\left|J_{\left(\xi_c^{(b)},\xi_c^{(A)},\xi_c^{(T)}\right)\to(S_c,A_c,Lag_c)}\right| = \left|J_{(S_c,A_c,Lag_c)\to\left(\xi_c^{(b)},\xi_c^{(A)},\xi_c^{(T)}\right)}\right|^{-1}$. Second, due to the triangular dependency structure of market share, arrival time of piracy, and international release timing, the Jacobian is upper triangular. Therefore, the cross-term drops out from the determinant of the Jacobian $\left|J_{(S_c,A_c,Lag_c)\to\left(\xi_c^{(b)},\xi_c^{(A)},\xi_c^{(T)}\right)}\right|$, and thus $\left|J_{(S_c,A_c,Lag_c)\to\left(\xi_c^{(b)},\xi_c^{(A)},\xi_c^{(T)}\right)}\right| = \left|J_{(S_c)\to\left(\xi_c^{(b)}\right)}\right|\left|J_{(A_c)\to\left(\xi_c^{(A)}\right)}\right|\left|J_{(Lag_c)\to\left(\xi_c^{(T)}\right)}\right|$.

The j,k-element of the (c,t)-*th* Jacobian $J_{(S_c)\to\left(\xi_c^{(b)}\right)}$ represents $\frac{\partial s_{jct}}{\partial \xi_{kct}^{(b)}}$ is

$$J_{j,k}^{(c,t)} = \begin{cases} -\int P\left(D_{ict} = j \middle| \tilde{\theta}_i, \mu_c^{(b)}\right) P\left(D_{ict} = k \middle| \tilde{\theta}_i, \mu_c^{(b)}\right) \mathrm{d}F(\tilde{\theta}_i) & \text{, if } j \neq k \\ \int P\left(D_{ict} = j \middle| \tilde{\theta}_i, \mu_c^{(b)}\right)\left[1 - P\left(D_{ict} = j \middle| \tilde{\theta}_i, \mu_c^{(b)}\right)\right] \mathrm{d}F(\tilde{\theta}_i) & \text{, if } j = k \end{cases}$$

Combining “share inversion” and change-of-variable through Jacobian transformation, the likelihood of the joint system can be evaluated.

2.5.3 MCMC Procedure

The joint posterior samples are obtained through a random walk Metropolis algorithm. I draw all of the parameters $\boldsymbol{\Theta}$ in each sampling iteration. The covariance matrix of the proposal distribution is chosen by trial-and-error to get close to the asymptotically-optimal acceptance rate of 0.234.

2.6 Results

First, I present the estimated parameters of the demand model in Table 2.1. The table lists the posterior means and standard deviations of each parameter by country. Most of the parameters in the demand model are reasonable. For example, all international markets have significantly negative parameters to the release delay, confirming the notion that movies are perishable goods, and that the longer the movie wait-to-release in an international model, the less box office the movie will generate in that market. Furthermore, the parameter to the number of weeks into a release window are negative in all four markets. This corroborates the empirical observation that box office revenue follows exponential decay patterns and that the majority of box office revenue is concentrated in the first two to three weeks. However, the coefficients to log production budget for the US and Mexico markets are puzzling. The significantly negative coefficients for these two markets implies that movies with higher production budgets generate less box office revenue, which runs contrary to conventional wisdom.

A larger coefficient to “Piracy: national language” would suggest that the consumers in the focal country have a stronger preference for pirated video consumption over in-theater consumption. I find that the US and Germany have a larger coefficient to “Piracy: national language” than Mexico and Russia. A plausible explanation is that consumers in Mexico and Russia consider the movie-going experience more than just a consumption of the content of the movie, but instead a special occasion.

A larger coefficient to "Piracy: other language" would suggest that the consumers in the focal country do not mind watching pirated videos that are not in the national language of that country. The finding that US has the smallest coefficient among the four markets suggests that U.S. consumers strongly dislike watching pirated videos dubbed in foreign languages. This finding is in line with the high level of monolinguals in US. On the other hand, I find that the consumers in Mexico, Germany, and Russia like foreign-language pirated copies as much as national-language ones. There are several plausible explanations to this counter-intuitive finding: 1) in Mexico, Germany, and Russia, a large number of foreign-language pirated copies are in English, and some consumers in these countries may have proficiency in English, 2) pirates or crowd-source often create and upload subtitle files to accompany a pirated copy after the pirated movie is made available online, and consumers in these countries may be more accustomed to foreign-language soundtracks with national-language subtitles.

Table 2.1 Estimated Parameters on the Demand Model

	US	Mexico	Germany	Russia
Int'l release lag (weeks)		**-0.079**	**-0.047**	**-0.031**
		(0.004)	(0.004)	(0.008)
Weeks into release window	**-0.602**	**-0.575**	**-0.317**	**-0.606**
	(0.012)	(0.023)	(0.028)	(0.095)
log production budget	**-0.204**	**-0.256**	**0.378**	**0.421**
	(0.003)	(0.006)	(0.034)	(0.050)
Genre: Sci-Fi / Fantasy	**0.168**	**0.077**	0.086	**-0.198**
	(0.074)	(0.0126)	(0.087)	(0.085)
Genre: Action	**0.046**	**0.078**	**0.233**	-0.020
	(0.013)	(0.010)	(0.009)	(0.022)
Genre: Adventure	0.025	0.023	0.003	0.162
	(0.013)	(0.037)	(0.134)	(0.124)
Genre: Family	-0.074	**0.084**	**0.198**	-0.049
	(0.069)	(0.014)	(0.026)	(0.012)
Genre: Comedy	-0.094	**0.125**	0.047	**-0.033**
	(0.079)	(0.028)	(0.109)	(0.017)
Genre: Horror	**0.186**	**0.075**	**0.131**	0.043
	(0.086)	(0.009)	(0.062)	(0.056)
Genre: Others	-0.010	-0.025	0.122	**-0.094**
	(0.033)	(0.063)	(0.069)	(0.028)

MPAA: R	**-0.043**	**-0.041**	-0.040	-0.071
	(0.019)	(0.015)	(0.169)	(0.090)
MPAA: PG	-0.031	-0.013	**0.239**	**-0.243**
	(0.020)	(0.013)	(0.016)	(0.021)
MPAA: G	**-0.145**	-0.247	-0.154	-0.032
	(0.068)	(0.129)	(0.235)	(0.112)
Piracy: national language	**2.068**	**0.923**	**1.771**	**0.851**
	(0.077)	(0.028)	(0.097)	(0.043)
Piracy: other language	**0.434**	**1.268**	**1.075**	**2.500**
	(0.023)	(0.040)	(0.023)	(0.097)
Outside option: Feb	0.211	**-0.251**	-0.278	-0.114
	(0.199)	(0.061)	(0.147)	(0.236)
Outside option: Mar	0.556	**-0.162**	0.003	**-0.517**
	(0.144)	(0.012)	(0.020)	(0.150)
Outside option: Apr	0.149	0.147	-0.276	-0.061
	(0.235)	(0.175)	(0.145)	(0.264)
Outside option: May	-0.007	0.387	**-0.133**	-0.226
	(0.325)	(0.313)	(0.067)	(0.169)
Outside option: Jun	0.142	0.273	0.008	-0.139
	(0.239)	(0.247)	(0.022)	(0.219)
Outside option: Jul	-0.158	-0.071	-0.296	0.070
	(0.412)	(0.052)	(0.158)	(0.340)
Outside option: Aug	**0.342**	**-0.157**	-0.496	-0.199
	(0.125)	(0.018)	(0.272)	(0.184)
Outside option: Sep	0.234	0.064	0.291	-0.022
	(0.187)	(0.130)	(0.184)	(0.288)
Outside option: Oct	-0.071	-0.041	-0.386	-0.080
	(0.362)	(0.067)	(0.212)	(0.255)
Outside option: Nov	-0.056	0.113	-0.179	0.160
	(0.353)	(0.155)	(0.091)	(0.392)
Outside option: Dec	0.265	**-0.091**	0.149	-0.122
	(0.168)	(0.041)	(0.102)	(0.229)

I In Table 2.2, I present the coefficients for the equation of number of weeks to first piracy in each market. The estimated intercepts suggest that piracy producers in the US, Germany, and Russia tend to produce and release camcorder pirated copies faster than the Mexico counterparts. I find that in the US, Mexico, and Russia, movies with higher production budgets tend to be pirated significantly faster than lower budget movies. This suggests that the production decisions of pirates are strategic—they prioritize producing pirated copies of movies with higher budgets. Note that the coefficient for the international release lag for the US is unidentified, because the international release lag is always zero, by construction, for U.S. data points.

Table 2.2 Estimated Parameters on Number of Weeks-to-First-Piracy

	US	Mexico	Germany	Russia
Intercept	**4.331**	**9.713**	2.647	**4.087**
	(0.738)	(2.592)	(3.210)	(1.199)
Int'l release lag (weeks)		0.030	**-0.076**	**0.032**
		(0.038)	(0.034)	(0.013)
log production budget	**-0.157**	**-0.467**	-0.043	**-0.182**
	(0.042)	(0.142)	(0.175)	(0.067)

In Table 2.3, I present the coefficients for the equation of number of weeks of lag in releasing a movie in an international market, relative to the US. I find that the year of release is not a consistently significant determinant of international release lags, contrary to my initial conjecture that technological adoption has sped up international release. As a result, a new exogenous shifter of international release lags is needed to handle endogeneity issues in the joint model.

Table 2.3 Estimated Parameters on Weeks of Lag in International Release Relative to U.S.

	Mexico	Germany	Russia
Intercept	-0.787	28.068	7.020
	(7.313)	(10.241)	(5.185)
log production budget	0.091	**-1.235**	-0.288
	(0.400)	(0.562)	(0.286)
Year: 2007	-0.586	-5.237	-0.772
	(1.618)	(3.197)	(1.166)
Year: 2008	-0.544	-1.601	-1.376
	(1.371)	(2.166)	(1.435)
Year: 2009	-0.095	-4.150	**-2.334**
	(1.343)	(2.238)	(0.982)
Year: 2010	-1.461	-4.055	-1.503
	(1.342)	(2.499)	(0.879)
Year: 2011	-1.407	-2.511	-1.238
	(1.3482)	(2.231)	(0.919)
Year: 2012	-1.042	-5.017	-1.563
	(1.685)	(2.858)	(0.989)
Year: 2013	-0.741	**-4.586**	-1.733
	(1.698)	(2.160)	(1.103)

2.7 Conclusion

I analyzed the cross-country cannibalization effect of movie piracy on international box office revenue in four major countries, using a random-coefficient logit model of aggregate demand. I find that, on average, consumers consider watching pirated copies to be as attractive as watching the movies in theaters. More importantly, I find that U.S. consumers dislike watching pirated videos in foreign languages, whereas consumers in three international markets find pirated videos in non-national languages acceptable. This finding suggests that studios should not delay movie releases in international markets; otherwise, piracy generated from the U.S. theatrical release will spill over and cannibalize the international box office revenue. The first weekend of theatrical release in a country is the most important time in the entire theatrical release window. Therefore, in the simultaneous global release setting, where a movie is released in the same weekend across all countries, the box office revenue of the first theatrical weekend from international markets would not be hampered by piracy originating from pirates filming the movie in U.S. theaters. Our analysis supports the recent strategy of studios moving to simultaneous global release scheduling.

2.8 References

Ainslie, A., Drèze, X., & Zufryden, F. (2005). Modeling Movie Life Cycles and Market Share. *Marketing Science*. Retrieved from http://pubsonline.informs.org/doi/abs/10.1287/mksc.1040.0106

Berry, S., Levinsohn, J., & Pakes, A. (1995). AUTOMOBILE PRICES IN MARKET EQUILIBRIUM. *Econometrica*, *63*(4), 841–890.

De Vany, A. S., & Walls, W. D. (2007). Estimating the Effects of Movie Piracy on Box-office Revenue. *Review of Industrial Organization*, *30*(4), 291–301. http://doi.org/10.1007/s11151-007-9141-0

Elberse, A., & Eliashberg, J. (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science*, *22*(3), 329–354. http://doi.org/10.1287/mksc.22.3.329.17740

Jiang, R., Manchanda, P., & Rossi, P. E. (2009). Bayesian analysis of random coefficient logit models using aggregate data. *Journal of Econometrics*, *149*(2), 136–148. http://doi.org/10.1016/j.jeconom.2008.12.010

Luan, Y. J., & Sudhir, K. (2010). Forecasting Marketing-Mix Responsiveness for New Products. *Journal of Marketing Research*, *47*(3), 444–457. http://doi.org/10.1509/jmkr.47.3.444

Ma, L., Montgomery, A. L., Singh, P. V., & Smith, M. D. (2014). An Empirical Analysis of the Impact of Pre-Release Movie Piracy on Box Office Revenue. *Information Systems Research*, *25*(3), 590–603. http://doi.org/10.1287/isre.2014.0530

Moretti, E. (2011). Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *The Review of Economic Studies*, *78*(1), 356–393. http://doi.org/10.1093/restud/rdq014

Nevo, A. (2000). A PRACTITIONER'S GUIDE TO ESTIMATION OF RANDOM-COEFFICIENTS LOGIT MODELS OF DEMAND. *Journal of Economics & Management Strategy*, *9*(4), 513–548.

Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing Bias in Observational Studies Using Subclassification on the Propensity Score. *Journal of the American Statistical Association*, *79*(387), 516–525.

Rossi, P. E., Allenby, G. M., & McCulloch, R. E. (2005). *Bayesian Statistics and Marketing*. John Wiley & Sons, Ltd.

Sawhney, M. S., & Eliashberg, J. (1996). A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures. *Marketing Science*, *15*(2), 113–131. http://doi.org/10.1287/mksc.15.2.113

Shah, D., Kumar, V., & Zhao, Y. (2015). Diagnosing Brand Performance: Accounting for the Dynamic Impact of Product Availability with Aggregate Data. *Journal of Marketing Research*, *52*(2), 147–165. http://doi.org/10.1509/jmr.13.0530

Train, K. E. (2003). *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press. http://doi.org/10.1017/CBO9780511753930

Walls, W. D. (2008). Cross-country analysis of movie piracy. *Applied Economics*, *40*(5), 625–632. http://doi.org/10.1080/13504850600707337

Chapter 3

Chapter 3: Bayesian Analysis of Color Preferences: An Application for Product and Product Line Design

When choosing which colors to offer in their product lines, firms often rely upon consumer preference models that do not account for the heterogeneity of their target market and do not consider the trade-offs consumers are willing to make for different color options. For this research we used visual conjoint analysis to assess preference for backpack color and then modeled respondent utilities with a Bayesian hierarchal multinomial logit model. This provided counter intuitive results in which product line color options are not additive but each color changes depending on the number of options the firm is willing to offer and that colors which seem to dominate secondary preferences within a target market may not be the best colors to choose for product line expansion.

3.1 Introduction

The popular press commonly points to aesthetics as key to the success of a variety of products from companies such as Apple, Harman/Kardon, Microsoft, and Nike (Carr 2013, Dadich 2014, Vanhemert 2014). It has been clearly demonstrated that the acceptance and adoption of new products are highly dependent upon aesthetics design (Berkowitz 1987, Bloch 1995). Product aesthetic can make up 40-90% of a consumer's purchases decision (Bacon and Butler, 1981). Product color is one of the key factors in product aesthetics; color's strong influence on purchase decision and its relatively low cost to vary in a product makes color an important driver for profitability of a product.

In light of the importance of color to product design and purchase decisions, which affect market share and profits, manufacturers rely upon industry associations, such as the Color Marketing Group (REF), to provide expert direction towards upcoming color trends. For example, the Pantone Fashion Color Report for Fall 2014 projected the yellow shade of Misted Yellow (14-0837) and a different shade called Custard (13-0720) for Spring 2015. Often, because the meaning of colors changes by context, companies employ color consultants to further aid in to make specific color decisions for their product lines. Color consultants typically rely on design heuristics, current trends, and their own intuition and experience to make recommendations about a product's aesthetics (Liu 2003). These creative experts start by proposing an initial set of colors based on available information and insights, and then they conduct market research on this initial set of colors to determine the sales potential of each tested color. The manufacturer then uses the result of the market research to either retest a different set of colors or determine product color choice.

Since product color is typically chosen from the limited number of tested colors from the market research, the firm can easily miss out on an untested color that would have been even more popular than any that were tested. The research presented in this paper demonstrates that a company can improve on the product color insights derived from the market research by exploiting the continuous nature of color.

Manufacturers often offer products with multiple color options. As long as costs of different colors are nontrivial, firms do not offer every person their own favorite color shade but instead provide multiple colors with the goal of offering alternatives that approximate preferences over the population. Therefore, the optimal set of colors for a product not only depends on the favorite colors of consumers but also depend on their utility for alternative colors. The following example illustrates the fact that choosing product colors in a product line based on popularity of each individual color can be suboptimal. Suppose the market consists of three customer segments in descending order of size. The firm conducts market research to with the intent of choosing two final color options. The firm tests three colors: dark blue, light blue, and red. Segment 1 likes dark blue the most and also likes light blue. Segment 2 prefers light blue but also likes the product in dark blue. Segment 3 strongly prefers red, with steep declines in utility for other colors. If applied to this example, the current color research practices would reveal that dark blue is the most popular color, while light blue would rank second, and red third. Should the firm choose to offer the product in dark blue and light blue, based on the popularity ranking, the firm would lose the sales to segment 3 who have very strong preference to red. This stylized example illustrates a case where the existing approaches are suboptimal. The optimal two color offerings would be dark blue and red, because there will be little loss of sales to segment 2, which still likes dark blue even though they prefer light blue to dark blue. This simple example demonstrates the need to consider utility among color alternatives in deciding optimal color offerings in the product line decision.

This research develops a choice model that exploits the continuity of colors and demonstrates the potential of leveraging this model for color choice in both single and multiple color options scenarios. We use a multinomial logit model with a non-linear utility function over a continuous color space, incorporating consumer preference heterogeneity through random-effects specifications in a hierarchical Bayesian model. Hierarchical Bayesian model with random-effects coefficients can represent consumer heterogeneity better than alternative methods such as latent class model (Arora, Allenby, and Ginter 1998). Using the posterior draws from the estimated choice model, we integrate over preference distributions to determine the optimal color options that maximize aggregate expected consumer utility in the target market.

The contribution of this research is two-fold. First, this research develops a choice model that exploits the continuity of colors and demonstrates the potential this color continuity has over the discrete color swatch approach in industry practice. Second, this research combines the choice model literature and product line design literature and demonstrates that this integrated approach allows manufacturers to better understand consumer color preference and to make better color choices when offering multiple color options within a single product line.

3.2 Literature

Research on color preference has primarily focused on determining the universal preference of color ordering, and the relationship between color preference and demographic factors such as gender or age group. Eysenck and colleagues (1941) conducted surveys with 40 adults and showed blue as the most preferred color universally and that gender has a small association with color preferences. Guilford and Smith (1959) conducted further studies and documented a universal ordering of preferences over 300 colors.

The bulk of color-related research over the past 40 years has focused on how consumers assess color (McManus et al. 1981, Holmes and Buchanan 1984, Smet et al. 2010, Schloss et al. 2013), how consumers respond emotionally to color (Garth 1922, Kanda 2004, Terwogt and Hoeslma 2005), and color preference heterogeneity via segmentation (Garth and Porter 1934, Harris 1989, Hurlbert and Ling 2007, Bakker et al. 2013, Baniani et al. 2014). The extant findings on consumer reaction highlight the importance of product line decisions in regards to color. Our research focuses not on the consumer reaction but on the firm's best decision with regard to color selection.

Ou and his coauthors (2004a) linked color preference to a subjective description of color (e.g. color emotions and color appearance.) Because this work was conducted in the context of understanding universal preferences for colors, their findings do not provide insight on the heterogeneity in individual color preference and on how to measure these individual preferences for the purpose of product design.

Many quantitative methods have been developed in the context of product design but are limited in providing guidance for colors. For example, the Quality Functional Deployment, or House of Quality (Hauser & Clausing, 1988) provides a means to translate customer needs to measurable technical requirements that designers can then attempt to maximize, minimize, or target to specific values. However, customer needs are specified in subjective factors such as "visually appealing". Affective design methods, such as Kansei (Nagamachi 1995), assess consumer qualitative preferences through the use of Likert scales and attempt to translate these into design directions and constraints. While these methods have generally found success, it has primarily been within the context of ergonomics and product form gestalt (Lugo et al. 2012). Methods like Kansei involve specifying color subjectively, treating colors in emotional qualities (e.g. "comfortable" or "dramatic") and perceptual attributes (e.g. "warm") instead of objective characteristics (e.g. "hue" or "luminance") (Hogg et. al., 1979, Hsiao, 1995, Lee, Luo, and Ou, 2008, Hanada, 2013). Specifying colors in subjective factors complicate the task of measuring color preferences from market research because each consumer may have different perception along these subjective dimensions (Ou et al. 2004b).

This research is built on the new product development literature that uses utility functions to specify product preferences. Utility models have long been used to capture product preferences and product design decisions (Green and Srinivasan, 1990), because such models make it possible to understand the relationship among attributes and identify worthwhile trade-offs (Thurston, 1991). Generally, when color is included in utility models, it has been included as a discrete variable (Alfnes 2006). The resulting measures simply reflect preferences among just those colors that have been rated, equivalent to the color swatch research currently used by color consultants.

Despite often being represented with indicator variables in discrete choice models, colors fall on a continuous spectrum. The continuous variable representation of color in utility models allows preference measurement of colors outside of a discrete set of colors shown to respondents, an important step forward for color research. Psychologists have long posited that color perception can be represented in three dimension where colors that appear similar in human perceptions are located close to each other in the three dimensional space (Krantz 1975). One widely-used color representation is the CIELAB color space (also known as LAB color space), in which each color is represented by its lightness, red-green, and blue-yellow (Abramov and Gordon 1994, Mollon 1982.) Like other color representations, the CIELAB color space produces over 16.8 million possible colors. This incredibly large space makes it virtually impossible to effectively explore consumer color preference using indicator variables in choice models or qualitative verbal representations. This is the primary scientific motivation for the research presented in this paper.

Figure 3.1 graphically shows how the color changes along the three dimensions of the CIELAB color space. One of the advantages of the CIELAB color space is that the red-green and blue-yellow dimensions are orthogonal (Abramov and Gordon, 1994). Abramov and Gordon suggest that red and green perception is distinct from yellow and blue perception partly due to physiological mechanism in humans. Another advantage of the CIELAB color space is that a change of coordinates in the color space yields similar magnitude of change in color perception by human regardless of the coordinates. The third advantage of the CIELAB color space is that this color space is device-independent. RGB color space is a well-known alternative to CIELAB color space, and is used widely in computer graphics. Each color in the RGB color space is defined by the additive combination of the red, green, and blue primary colors. The RGB color space is embedded in the CIELAB color space, and thus the CIELAB color space captures all the colors in the RGB color space and other colors outside of the RGB space. CMYK is another well-known color space primarily used in color printing. Each color in CMYK is defined by the amount of cyan, magenta, yellow and black inks to be mixed. Similar to RGB color space, the CMYK color space is a subspace of the CIELAB color space. In fact, CIELAB color space can describe all the colors visible to the human eye and is one of the largest standard color spaces, representing more colors than other commonly used color spaces. One practical limitation of the CIELAB color space is that the CIELAB color space includes non-physical colors that cannot be produced by physical light source. Despite this limitation, the CIELAB color space is an important theoretical construct for analyzing human perception of colors. The CIELAB color space has been used in recent consumer research on color preferences (Deng et al. 2010). The research presented in this paper models consumers' color preference over the CIELAB color space and focuses the analysis on the physical colors within the CIELAB color space.

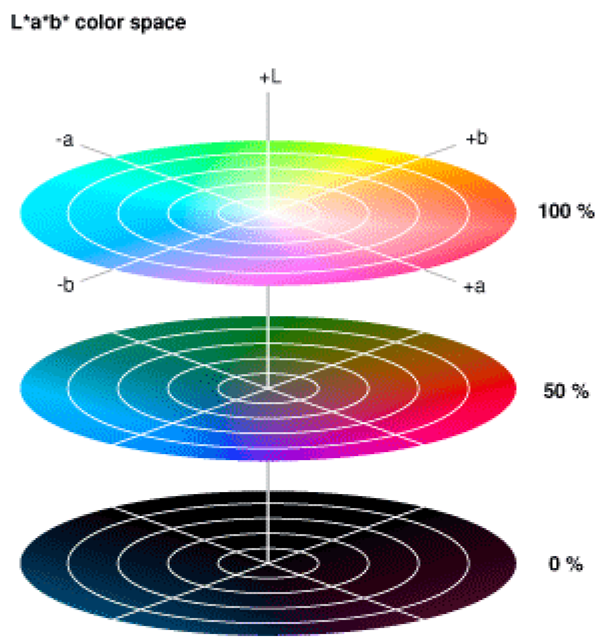


Figure 3.1 Color representation of the CIELAB color space

The L dimension represents lightness; the A dimension represents redness/greenness; the B dimension represents yellowness/blueness. Source of figure: https://developer.apple.com/library/mac/documentation/cocoa/conceptual/DrawColor/Concepts/AboutColorSpaces.html

Manufacturers often offer multiple color options for a product, and this research addresses the product line selection problem while building on previous research in this area. Choosing the color options is in essence positioning a product line in a horizontal differentiation setting. Page and Rosenbaum (1987) demonstrated a product line redesign application in which the market share optimization was performed through simulation on consumer preferences estimated from conjoint analysis. They focused only on the functional attributes of consumer kitchen appliances, not considering aesthetics. McBridge and Zufryden (1988) applied an integer-programming technique to find the product line selection that maximizes seller's return, also focusing on the functional aspects of consumer products while neglecting any aesthetic attributes. Dobson and Kalish (1993) developed a heuristic for finding a product line that maximize profit or total welfare based on conjoint analysis. There are many researches on using various optimization method to derive the optimal product line (Nair et al 1995, Shi et al 2001, Belloni et al 2008). When addressing the manufacturer's problem of product line design in the color setting, the research presented in this paper focuses on accounting for the substitutability among product color in the consumer purchase decision. Choice-set dependent effects are not modeled nor assortment effects that may complicate the problem of product line selection (Simonson and Tversky 1992, Kalyanam, Borle, and Boatwright 2007).

3.3 Method Overview

The method used in this research to determine consumer preference function for color can be generalized outside the specific context that we are using and is based upon commonly accepted quantitative consumer research methods. First, a choice study is created from a design of experiments. In our example, colors are separated into three variables which in turn produces a study with 25 different color combinations presented as 25 questions, each with three options. An additional set of questions, five in our example, is created for a hold-out sample to later test the validity of the derived utility function. The choice study for this research was presented digitally online but could just as easily been presented physically in person. After respondents finish their choice survey, their individual responses are analyzed using a hierarchal Bayesian multinomial logit model with splines, to be discussed in more detail later. The result of the analysis is a function that matches an individual's preference for color for the specific product line. This set of preference functions, one for each individual, is then aggregated to determine the optimum set of colors for the product line. The rest of this article will discuss the various steps of this method in detail within the context of a particular product line.

3.4 Data

To provide context for this research, the model is applied to survey data about backpack colors. In this study, a hypothetical backpack manufacturer is interested in the color options to produce. This manufacturer conducts a study to elicit the color preference from the target market and make an informed design decisions about which color options should be produced for retail sale.

Backpacks were chosen to serve as the product domain for multiple reasons. First, backpacks can and do come in almost every conceivable color. This broadly existing design space eliminates external constraints that would complicate the design of experiments. Secondly, research has shown that color can play an even more important role in purchase decisions when competing product choices are not considerably different from one another on other dimensions (Grossman & Wisenblit, 1999), as is the case with backpacks. In this experiment, color is the only differentiator between backpack choices provided. Third, the study was administered to students on a university campus; a high usage segment of backpacks. Fourth, the price of backpacks is non-trivial for the majority of students, increasing respondent level of involvement in the choice of backpack. Finally, given the variation of backpack colors in the marketplace, it is expected that backpack color preferences will be heterogeneous.

The research method used conjoint analysis to investigate the preference of colors in the context of aiding product design. A choice-based conjoint analysis study was presented to a sample of 291 students in a university freshman-level engineering class. This sample of respondents consisted of 215 men and 76 women and more than 90% of the respondents were between 18 and 21. Each respondent answered all 25 questions, where each question showed three backpacks, each with a different color choice, and the respondent was asked to choose the most preferred color in each question (Figure 3.2). The color choices in the 25 questions were chosen by a balanced, orthogonal fractional factorial design from 125 colors. The research method for determining consumer response involved each respondent answering questions within an online survey. Since computers represent colors in the RGB color space, the set of colors were chosen in uniform spacing in the RGB color space. As stated previously, RGB is a subset of the CIELAB space, which was used for the utility preference analysis. All participants were given the same set of questions, but the order of questions was randomized for each participant so that fatigue or learning effects would not be confounded with specific colors. Even though incorporating prior estimates of consumer preferences in the design of choice experiments can lead to improve design efficiency and yield more accurate predictions (Arora and Huber 2001), we adopted the traditional experimental design because color preferences vary significantly across products and therefore other published study may not provide reasonable prior information to guide Bayesian experimental design.

Figure 3.2 Example question from backpack color study

In addition to the main survey, respondents were invited to complete a follow-up survey several days after completion of the main survey. All of the respondents returned for the follow-up survey. In the follow-up survey, each respondent was asked 5 questions in the same choice-based conjoint format as the main survey. The purpose of the follow-up survey was to provide a holdout sample for model evaluation. Respondents were not allowed to immediately take the follow-up survey. The purpose behind the several day wait between the main survey and the follow-up survey was to reduce any bias from memory effect.

3.5 Modeling Color Utility

We used a hierarchal Bayesian multinomial logit model with splines was used to study the color preferences in the data. Multinomial logit modeling has been used widely in marketing literature (Guadagni and Little 1983, Hardie, Johnson, and Fader 1993) and the hierarchal Bayesian multinomial logit formulation enables a natural incorporation of heterogeneity and an improvement of coefficient estimates through pooling information from other observations (Rossi, McCulloch, and Allenby 1996).

We use natural cubic splines to model the relationship between utility and color attributes allow this relationship to be nonlinear and smooth. Natural cubic splines are piecewise cubic polynomials with continuous first and second derivatives at the knots. The function fitted from natural cubic spline is linear beyond the boundary knots. In other words, the surface fitted by natural cubic spline are smooth in the entire feature space. In contrast to this method's focus on a smooth function, the linear spline basis in Kim, Menzefricke, and Feinberg (2007)'s conjoint analysis of bathroom scales data yielded a non-smooth utility function over the features. This research emphasizes the smoothness of the utility function over color space because it is natural for consumers to have a gradual and smooth change in utility over color. This is presumed since the continuous color space is so large each adjoining color is barely imperceptible from its neighbor and therefore an abrupt change in utility is highly unlikely. Four interior knots were chosen for each color attribute. Alternative spline parameterizations were explored as a robustness check. Consumer heterogeneity is modeled with a multivariate normal distribution on the coefficients for the basis represented lightness, redness, and yellowness.

This model assumes the deterministic component of the utility for a color option to depend on the lightness, red-green value, and yellow-blue value of the color. As discussed earlier, these 3 components are the canonical coordinates of the CIELAB color space.

The random utility of individual i that chooses backpack j in question k is

$$U_{ijk} = f\left(L_{jk}, A_{jk}, B_{jk}\right) + \varepsilon_{ijk}$$

where L_{jk} , A_{jk} , B_{jk} is the lightness, redness, and yellowness of the backpack j in survey question k.

Furthermore, the utility function specification should be flexible to allow diversity of color preferences over the CIELAB space. To allow for a smooth and flexible utility function, the function of utility in color space is modeled by an additive natural cubic spline representation of the lightness, redness, and yellowness.

$$f\left(L_{jk}, A_{jk}, B_{jk}\right) = \sum_{q_L=1}^{Q_L} \lambda_{q_L i} \ N_{q_L}\left(L_{jk}\right) + \sum_{q_A=1}^{Q_A} \alpha_{q_A i} \ N_{q_A}\left(A_{jk}\right) + \sum_{q_B=1}^{Q_B} \beta_{q_B i} \ N_{q_B}\left(B_{jk}\right)$$

where Q_L is the number of knots for lightness, Q_A is the number of knots for redness, Q_B is the number of knots for yellowness, λ's, α's, β's are the set of coefficients to the basis represented lightness, redness, and yellowness, $N_q(\bullet)$ is the q-th basis function of natural cubic spline defined as

$$N_1(x) = 1$$

$$N_2(x) = x$$

$$N_{q+2}(x) = d_q(x) - d_{q-1}(x)$$

$$d_q(x) = \frac{\left(x - \xi_q\right)_+^3 - \left(x - \xi_Q\right)_+^3}{\xi_Q - \xi_q}$$

A notable feature of natural cubic spline is that the function outside of the two boundary knots is linear whereas the represented function inside the boundary knots is non-linear. This feature helps alleviating the issue of erratic extrapolation of preference for color outside of tested color spaces (Hastie, Tibshirani, and Friedman 2009, Chapter 5).

We selected the number and locations of knots through model selection, unlike the approach in Kim, Menzefricke, and Feinberg (2007) where the number and locations of knots were estimated jointly with the model parameters. Analysis of the model performance in our model selection suggests that the joint estimation approach for knot number and location is unlikely to yield substantial benefit in our data.

Heterogeneity in preference across respondents is captured by a random effects specification

$$\theta_i \sim Normal(\bar{\theta}\,, \Lambda)$$

, where $\theta_i = (\lambda_{1i}, \ldots, \lambda_{Q_L i}, \alpha_{1i}, \ldots, \alpha_{Q_A i}, \beta_{1i}, \ldots, \beta_{Q_B i})'$

In other words, the individual parameters for the components of the color preferences are distributed normally from the population means with a covariance of Λ. This covariance matrix relates to the magnitude of heterogeneity of color preference across respondents.

The survey questions enforce respondents to choose their favorite color among 3 color choices, and thus an outside option is not accounted for in this model. The “none” option essentially would enable the measurement of the difference between the utility of the outside option and the utility of the colored backpack. We explicitly excluded the “none” option in part because there was no outside option concept in this study, rather it was a choice of “best in set.” The none option would be more relevant (more defined) in an experiment if prices for the colors were included, so that the “none” option would correspond to keeping the money instead of purchasing. As an additional consideration, this difference of the utilities, between the outside option and a colored backpack, depends on other attributes that may not be available in the color decision of product design phase. For example, when choosing color for a new product, the firm may not have yet decided on the selling price, the positioning, or even the list of features of the new product, and thus the comparison of the focal product with outside option is ill-defined.

3.6 Estimation Results

3.6.1 Model Selection

We used the data are used to estimate the proposed model and two alternative spline specifications. The proposed model is a multinomial logit model with a 4-knot natural cubic spline representation of color attributes. The first alternative model includes two-way interactions in additional to the natural cubic splines. The second alternative model uses a 5-knot natural cubic spline representation. Comparing the model performance of the first alternative model to the proposed model provides insight on the necessity of including interaction terms in modeling the color preferences; comparing the model performance of the second alternative model to proposed model enables a judgment of whether the proposed model is flexible enough to account for the non-linearity of the color preferences.

A Markov chain Monte Carlo (MCMC) method is used for estimating the models. Sampling chain was run until convergence. Convergence was verified using multiple parallel chains with different starting values.

For each participant, 5 follow-up questions similar to the main survey were asked. These questions and answers were used for out-of-sample prediction. All models have holdout hit rates that are significantly above 33% chance, the accuracy of random guessing. The proposed model has significantly higher holdout hit rate, as demonstrated in Table 3.1, than alternative models with 2-way interactions or with more knots, suggesting that adding interaction terms overfit the color preference function and 4 interior knots are sufficient to handle the nonlinearity of the color preference function. It is concluded from the robustness check that the number of interior knots in the proposed model is sufficient and the main effect only specification is acceptable.

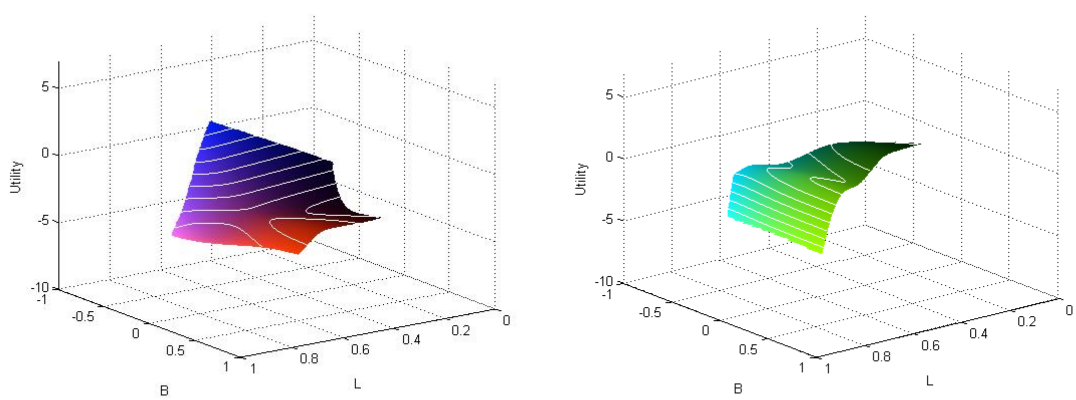
Table 3.1 Log-likelihood and holdout hit rate of the three competing models

Holdout Hit Rate Suggested that the Proposed Model has the Highest Predictive Validity.

	Proposed Model	Alternative Model with Interaction	Alternative Model with more knots
Spline basis	Natural cubic spline	Natural cubic spline	Natural cubic spline
Number of interior knots for each color attribute	4	4	5
Interaction between color attributes	No	2-way	No
Log-likelihood	-4334.8	-3624.0	-4202.2
Holdout hit rate (%)	65.9	63.3	60.6

3.6.2 Utility of Color

With a clearly defined preference model for color, it helpful to demonstrate graphically the utilities of color along the 3 dimensions of the color space. While it may be easier to mathematically represent the 3-dimensional CIELAB color space, it is difficult to visually represent this complex color space and its associated utility preference. Because of this difficulty, each plot below shows the utilities across 2 horizontal dimensions, fixes the remaining color dimension at a chosen value, and uses the vertical dimension to represent utility. Respondent #2 is used for an explanatory example in Figure 3.3. Figure 3.3(a) plots the utilities of colors over two of the three dimensions of the CIELAB color space. The redness value (A) is fixed at 0.4. The vertical z-axis represents the utility of a specific color. The x-axis on the left represents the yellowness (the B-dimension) of the color. The y-axis on the right represents the lightness (the L-dimension of the color). A more negative value on the x-axis (B dimension), that is further to the left of the plot, represents a more blueish color. A more positive value on the x-axis, that is further to the right of the plot, represents a more yellowish color. A larger value on the y-axis (L dimension), that is further to the left of the plot, represents a lighter color. A smaller value on the y-axis (L dimension), that is further to the right of the plot, represents a darker color. Each white contour line denotes the colors that give equal utility to respondent #2. From the contour lines in Figure 3.3(a), we see that the utility slopes downward from the blue regions to purple regions and then flattens out in the red regions. This means respondent #2 prefers blue over purple and red, and is relatively indifferent between light purple and red.



(a) (b)

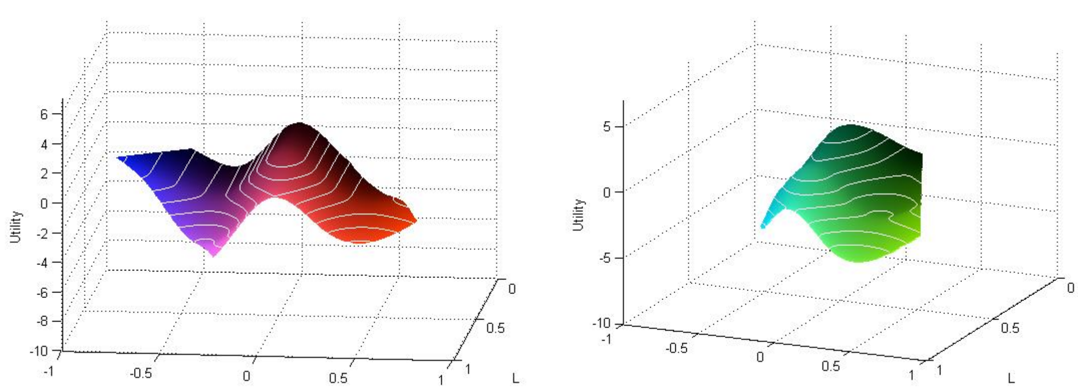
Figure 3.3 (a) and (b) Utilities of colors along the yellowness (B) and the lightness (L) dimensions for respondent #2.

Positive value on the yellowness (B) dimension represents a yellowish color; Negative value on the yellowness (B) dimension represents a blueish color. Larger value on the lightness (L) dimension represents brighter color; Smaller value on the lightness (L) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (A) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (A) equal to -0.4. The plotted surface is limited to the subset of physical colors.

Figure 3.3(b) is a similar plot to Figure 3.3(a) except the redness value (A dimension) is fixed at -0.4 in Figure 3.3(b) rather than at 0.4, where it was in Figure 3.3(a). Again, the purpose of this plot is to help visualize the respondent's utility for particular colors. The contour lines in Figure 3.3(b) show that the utility surface slopes downward gently from dark green to green and then falls off steeply from green to light green. From this plot, it can be interpreted that respondent #2 slightly prefers dark green over green, and strongly prefers green over light green and light blue, which are equally not preferred.

Recall that a unit change in distance between two points in the CIELAB space lead to a constant change in relative differences in color perception. Figures 3.3(a) and 3.3(b) show that in different regions of color the utility surfaces have different degrees of change. This varying degree of change over the unit distance across color regions supports the proposed flexible and nonlinear model specification.

To demonstrate the heterogeneity in color preferences the utility plots of different respondents are analyzed. Figures 3.3(a) and (b) show the color preference of respondent #2; Figure 3.4(a) and (b) show the color preference of respondent #27; Figure 3.5(a) and (b) show the color preference of respondent #30.



(a) (b)

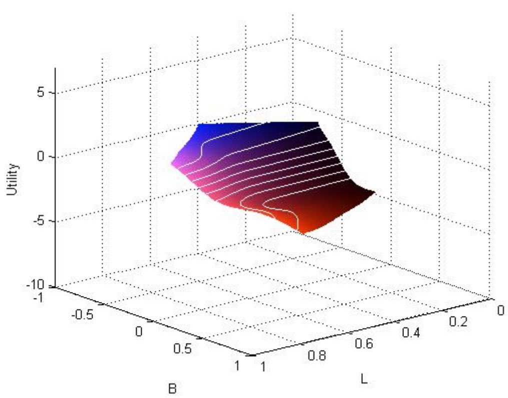
Figure 3.4 (a) and (b) Utilities of colors along the yellowness (B) and the lightness (L) dimensions

for respondent #27.

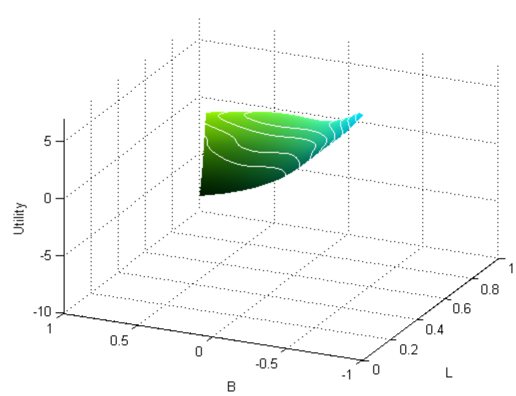
Positive value on the yellowness (B) dimension represents a yellowish color; Negative value on the yellowness (B) dimension represents a blueish color. Larger value on the lightness (L) dimension represents brighter color; Smaller value on the lightness (L) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (A) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (A) equal to -0.4. The plotted surface is limited to the subset of physical colors.

Figure 3.4(a) shows a group of valleys and peaks in the utility surface for respondent #27. This respondent primarily prefers red as this is the highest peak on the contour plot and also shows a strong secondary preference for blue. Purple and orange are located at level contours within the valleys, showing that they are equally preferred at a lower utility than either blue or red. Figure 3.4(b) shows that respondent #27 uniquely prefers green over teal and dark green, and likes light green the least among the variations in green colors.

The vast difference in the shape of the utility surface between Figures 3.3(a) and 4(a) and Figures 3.3(b) and 3.4(b) indicates strong heterogeneity in the color preference across respondents. The proposed model captures the preference heterogeneity through individual-specific coefficients. Furthermore, this model enables varying non-linear shapes of utility surface because the model parameterizes the color space through a spline representation.



(a)



(b)

Figure 3.5 (a) and (b) Utilities of colors along the yellowness (B) and the lightness (L) dimensions for respondent #30.

Positive value on the yellowness (B) dimension represents a yellowish color; Negative value on the yellowness (B) dimension represents a blueish color. Larger value on the lightness (L) dimension represents brighter color; Smaller value on the lightness (L) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (A) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (A) equal to -0.4. The plotted surface is limited to the subset of physical colors.

It should be noted that there are some potential limitations to such a simple preference model. For example, the backpack strap remains a constant color black. While this was intentionally kept constant to minimize interaction effects between the color of the strap and the color of the backpack it must be recognized that some colors may be more or less preferred due to the relationship between the color of the backpack and the strap. Future work will look into how the color preference model changes when more than one color is modified in a product line.

3.6.3 Favorite Colors of the Respondents

In the previous section we showed that the respondents have heterogeneous color preference. With this in consideration, it seems that the best approach is not to model a single utility function for the entire sample population due to the lack of homogeneity. Rather, in this section there is an exploration of the favorite colors of the individual respondents as predicted by the model. Figure 3.6 shows the predicted favorite color for each individual from the study in the CIELAB color space. The plots in Figures 3.3 through 3.5 were a representation of ranges of colors with the vertical axis demonstrating peak utility. The axes for Figure 3.6 are the 3 color coordinates (L, A, and B) with the color shown being the peak color from an individual's color preference plot. To phrase it another way, each point in the figure represents an individual and the color of the point is the color with highest predicted expected utility for that particular individual. The model predicts that a substantial portion of respondents favor darker colors for backpacks, such as black (near the bottom of the scatter plot) and charcoal (in the center of the scatter plot). Many individuals favor blue, red, or green backpacks.

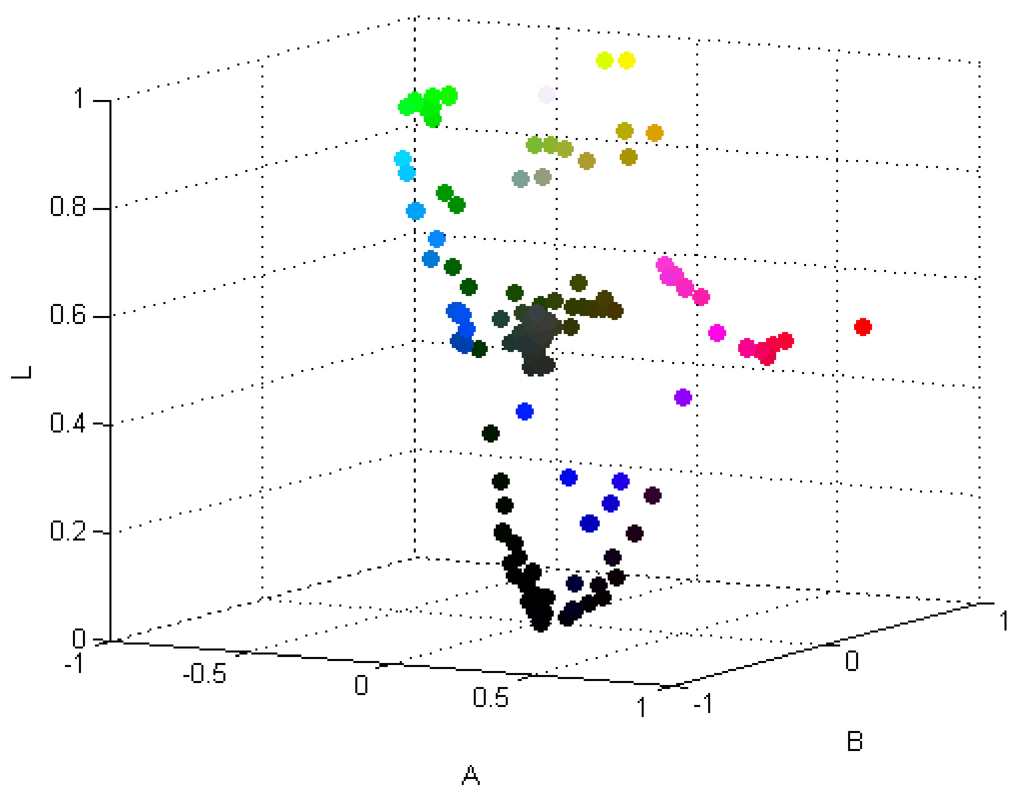


Figure 3.6 Scatter plot of the favorite color of each of the 291 respondents as predicted by the model

Each dot shows the favorite color for one individual and the coordinates of that color in the CIELAB color space.

3.6.4 Optimal Color Options Selection

Figure 3.6 shows that there is a large variety of favorite colors among the respondents, and more generally, in the target market. This diverse color preference suggests that offering only one color option may not be a good decision for the firm. In fact, manufacturers often offer several color options for a product. For example, a consumer can choose among red, blue, grey, black, white, green, and an orange color for a 2015 MINI Cooper. Knowing the optimal set of colors to manufacturer is important – offering color options that are too similar to each other takes up production line and increases expenses but may not improve sales. When the firm decides to offer multiple color options, it needs to determine which colors to offer. To address this important product line design decision, the potential of using the estimated model in determining the optimal color options is demonstrated.

The primary focus of this research is on the problem of choosing the set of color choices conditional on the number of color options to be offered. It is assumed that the firm has decided how many color options to offer based on considerations about manufacturing capabilities and expenses and the distribution channel. The number of color options is not endogenously modeled in this work because the decision of the quantity of color options would depend on information such as marginal costs in manufacturing additional color options and marginal costs in expanding shelf space in both warehousing and retail. The method employed for arriving at the recommended set of color options is to find the set of color options that maximizes the total expected utility of the entire set of participants. The optimal color options are not derived by maximizing market share. The rationale behind this choice of objective function is that the outside option is often ambiguous in the color decision stage of product design and the comparison of focal product to an outside option may depend on factors that are not finalized in the color decision stage. In summary, this work uses the estimated color preference model to guide the manufacturer's process by searching for the best set of color options that maximize the sum of expected utility for a set of color options in the set of participants (Table 3.2).

Table 3.2 Estimates of the population-level parameter color preference coefficients

The significant estimates have been marked with an asterisk, where the estimates are deemed significant when the 95% posterior interval does not contain zero.

Population-level Parameter	Posterior mean (95% confidence interval)
λ_1 coefficient to the 1st basis function representing lightness of color	0.244 (-0.260 0.748)
λ_2 coefficient to the 2nd basis function representing lightness of color	-31.732 (-37.755 -25.858)
λ_3 coefficient to the 3rd basis function representing lightness of color	87.006 (71.175 103.053)

λ_4 coefficient to the 4th basis function representing lightness of color	-241.941(-278.474 -206.471)
λ_5 coefficient to the 5th basis function representing lightness of color	306.772 (260.157 354.064)
α_1 coefficient to the 1st basis function representing redness of color	1.940 (1.182 2.770)
α_2 coefficient to the 2nd basis function representing redness of color	3.329 (-1.588 7.944)
α_3 coefficient to the 3rd basis function representing redness of color	-260.85 (-305.014 -218.953)
α_4 coefficient to the 4th basis function representing redness of color	317.770 (274.897 362.668)
α_5 coefficient to the 5th basis function representing redness of color	384.407 (329.707 441.748)
β_1 coefficient to the 1st basis function representing yellowness of color	-3.812 (-4.436 -3.212)
β_2 coefficient to the 2nd basis function representing yellowness of color	62.103 (52.457 71.948)
β_3 coefficient to the 3rd basis function representing yellowness of color	-166.005 (-192.006 -140.145)
β_4 coefficient to the 4th basis function representing yellowness of color	35.717 (20.000 50.272)
β_5 coefficient to the 5th basis function representing yellowness of color	129.425 (109.560 149.318)

Table 3.3 shows the optimal color options as a function of number of desired color options, derived from optimization over the total expected utility predicted by the model. The model suggest that the firm should offer a charcoal backpack if the firm decides to offer only one color option. If the firm would offer two color options, charcoal and green would be the best combination. The best three color options combination is charcoal, green, and black. The best four colors options combination is charcoal, green, black, and magenta. Note that the shade of green in the best four color options is lighter from that in the best three color options. This shows that the optimal expansion of the color options is more than adding an extra color to the set of chosen color options in a step-wise manner. The reason is that the addition of the fourth color option allows the manufacturer to segment the market further. The fourth color option removes the need of the firm to offer a darker shade of green that is moderately liked by a large number of target customers. Instead the expanded option enables the firm to offer colors, including light green and magenta,

that better satisfy segments in the target market. A naïve method to choose the optimal color options is to use popular favorite colors. Based on the insight drawn from Figure 6 that illustrates the favorite color of each respondent, the manufacturer may naively decide to include blue in the multi-color options combination because blue is a color that is favored by a substantial proportion of respondents. However, this naïve decision is suboptimal because color popularity does not account for the relative utility level among colors for the individuals. For example, even though some respondents favor blue the most, they also like charcoal moderately whereas the respondents who favor green the most strongly dislike charcoal. In this case, offering green as the alternative color option to charcoal would satisfy more consumers than offering blue as the alternative to charcoal. Therefore, a green and charcoal backpack lineup would improve the aggregate utility in the market more than a blue and charcoal backpack lineup.

Table 3.3 Optimal color options and the predicted aggregate utility as a function of number of color options to be offered

# of color options	Optimal Color Option(s)	Total Expected Utility
1	Charcoal	814.9
2	Charcoal Green	1053.2
3	Charcoal Green Black	1121.0

4	Charcoal, Green, Black, Magenta	1176.4

There are significant improvements in total expected utility if the backpack manufacturer expands the backpack offering from one color to two colors and from two to three, as shown in Table 3.3. As one would expect, adding color options increases the total utility because some consumers would be able to find a better matching product when there are more choices. On the other hand, the addition of the fourth color option does not improve the total utility as dramatically as the addition of the second and third options, suggesting diminishing marginal return of expanding the color options for the manufacturer. The number of color options the manufacturer chooses to offer should strike a balance between increasing demand by capturing the diverse color preference of consumers and increasing cost of manufacturing and carrying more color options. The analysis suggests that manufacturers can use the proposed method to improve the quality of the decision-making for color options of their new products.

3.7 Conclusion

Color is an integral part of product design. In practice, manufacturers often have to make decision on not just one color, but multiple color options for their products. The research presented in this paper demonstrates empirically the advantage of combining a hierarchical multinomial logit model with constrained optimization to assist manufacturers in understanding the color preferences in the target market and optimizing the set of color options to put to market. If the consumers in the target market have more diverse color preference, it may be beneficial for the firm to expand its product line and offer more color options. Of course, the choice of color options for a particular product line is context and time dependent. To maximize their effectiveness, manufacturers should use this model to assess consumer color preference for each new product cycle. Firms should also not assume that consumer preference for a particular product, like backpacks, will automatically translate to color preference for other products, like automobiles, even within the same target market.

We found that consumers' color preferences for backpack are nonlinear, and the spline modeling approach was able to accommodate the nonlinearity. Furthermore, the analysis found heterogeneity in color preference in a backpack setting.

One future extension of research could investigate the difference in willingness-to-pay among colors. By including prices in the questions of the conjoint analysis, researchers would be able to draw inferences for how much consumers are willing to pay extra for their favorite colors or how much they might sacrifice in choosing colors of preferred, but secondary, preference. Another possible extension of this research would be to compare color preference between product domains for the same target market. This would demonstrate that while the model is accurate within a specific context, a complete understanding of a consumer's color preference requires a variety of product contexts to be explored. It may even demonstrate, in support of historical research, that there are some universal color preferences.

3.8 References

Abramov, I., J. Gordon. 1994. Color appearance: On seeing red—Or yellow, or green, or blue. *Annual Review of Psychology* **45** 451–485.

Alfnes, F., A. G. Guttormsen, G. Steine and K. Kolstad. 2006. Consumers' Willingness to Pay for the Color of Salmon: A Choice Experiment with Real Economic Incentives. American Journal of Agricultural Economics 88(4) 1050-1061.

Allenby, G. M., P. J. Lenk. 1994. Modeling household purchase behavior with logistic normal regression. *Journal of American Statistical Association* **89** 1218-1231.

Arora, N., G. M. Allenby, J. L. Ginter. 1998. A Hierarchical Bayes Model of Primary and Secondary Demand. *Marketing Science* **17**(1) 29-44.

Arora, N., J. Huber. 2001. Improving Parameter Estimates and Model Prediction by Aggregate Customization in Choice Experiments. *Journal of Consumer Research* **28**(2) 273-283.

Bacon, F. R., T. W. Butler. 1981. *Planned innovation: A dynamic approach to strategic planning and the successful development of new products*. Industrial Development Division, Institute of Science and Technology, University of Michigan, Ann Arbor.

Bakker, I., van der Voordt, T., Vink, P., de Boon, J. and Bazley, C. (2013), Color preferences for different topics in connection to personal characteristics. Color Res. Appl.. doi: 10.1002/col.21845

Baniani, M. and Yamamoto, S. (2014), A comparative study on correlation between personal background and interior color preference. Color Res. Appl.. doi: 10.1002/col.21906

Belloni A., R. Freund, M. Selove, D. Simester. 2008. Optimizing Product Line Designs: Efficient Methods and Comparisons. Management Science **54**(9) 1544-1552.

Berkowitz, M., 1987, "Product Shape as a Design Innovation Strategy," Journal of Product Innovation Management, 4(4), pp. 247-283.

Bloch, P. H., 1995, "Seeking the Ideal Form: Product Design and Consumer Response," Journal of Marketing, 59(3), pp. 16-29.

Carr. A., 2013, February, Nike: The No. 1 Most Innovative Company of 2013, *Fast Company*, Retrieved from www.fastcompany.com.

Dadich, S., 2014, October, Design Your Day, *Wired Magazine*, 22(10), pp. 89-100

Deng, X., S. K. Hui, J. W. Hutchinson. 2010. Consumer preferences for color combinations: An empirical analysis of similarity-based color relationships. *Journal of Consumer Psychology* **20**(4) 476-484.

DiCiccio, T. J., R. A. Kass, A. E. Raftery, L. Wasserman. 1997. Computing Bayes' factors by combining simulation and asymptotic approximations. *Journal of the American Statistical Association* **92** 903-915.

Dobson, G. , S. Kalish. 1993. Heuristics for pricing and positioning a product line using conjoint and cost data. *Management Science* **39**(2) 160-175.

Eysenck, H. J. 1941. A Critical and Experimental Study of Colour Preferences. *American Journal of Psychology* **54** 385-394.

Garth TR. The color preference of five hundred fifty-nine full blood Indians. J Exp Psychol 1922;5:392–418.

Garth TR, Porter EP. The color preference of 1032 young children. Am J Psychol 1934;46:448–451.

Green, P. E., V. Srinivasan. 1990. Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice. *Journal of Marketing* **54**(4) 3-19.

Grossman, R. P., J. Z. Wisenblit. 1999. What We Know About Consumers' Color Choices. *Journal of Marketing Practice* **5**(3) 78-88.

Guadagni, P. M., J. D. C. Little. 1983. A Logit Model of Brand Choice Calibrated on Scanner Data. *Marketing Science* **2**(3) 203-38.

Guilford, J. P., P. C. Smith. 1959. A System of Color-Preferences. *American Journal of Psychology* **72** 487-502.

Hanada, M. 2013. Analyses of color emotion for color pairs with independent component analysis and factor analysis. Color Research and Application 38 297–308

Hardie, B. G. S., E. J. Johnson, P. S. Fader. 1993. Modeling Loss Aversion and Reference Dependence Effects on Brand Choice. *Marketing Science* **12** 378-394.

Harris LJ. Two sexes in the mind: Perceptual and creative differences between women and men. J Creat Behav 1989;23:14–25.

Hauser, J. R., D. Clausing. 1998. The House of Quality. *Harvard Business Review* 63-73.

Hastie, T., R. Tibshirani, J. Friedman. 2009. *The Elements of Statistical Learning*. Springer New York. doi: 10.1007/978-0-387-84858-7

Hogg J, Goodman S, Porter T, Mikellides B, Preddy DE. 1979. Dimensions and determinants of judgements of colour samples and a simulated interior space by architects and non-architects. British Journal of Psychology 70(2) 231-42.

Holmes CB, Buchanan JA. Color preference as a function of the object described. Bull Psychon Soc 1984;22:423–

425.

Hsiao, S.-W. 1995. A systematic method for color planning in product design. Color Research and Application 20 191–205.

Hurlbert AC, Ling Y. Biological components of sex differences in color preference. Curr Biol 2007;17:623–625.

Kalyanam, K., S. Borle, P. Boatwright. 2007. Deconstructing Each Item's Category Contribution. *Marketing Science* **26**(3) 327-341.

Kanda T. Analysis of human feelings to colors. Knowledge-Based Intelligent Information and Engineering Systems, Lecture Notes in Computer Science, Vol. 3215; 2004. p 143–150.

Kim, J. K., U. Menzefricke, F. M. Feinberg. 2007. Capturing Flexible Heterogeneous Utility Curves: A Bayesian Spline Approach. *Management Science* **53**(2) 340-354

Krantz, D. H. 1975. Color measurement and color theory: I. Representation theorem for Grassmann structures. *Journal of Mathematical Psychology* **12** 283−303.

Krantz, D. H. 1975. Color measurement and color theory: II. Opponent colors theory. *Journal of Mathematical Psychology* **12** 304−327.

Lee, W.-Y., Luo, M. R. and Ou, L.-C. 2009. Assessing the affective feelings of two- and three-dimensional objects. Color Research and Application 34 75–83.

Liu, Y. 2003. Engineering Aesthetics and Aesthetic Ergonomics: Theoretical Foundations and a Dual-Process Research Methodology. *Ergonomics* **46**(13-14) 1273-1292.

Lugo, José E., Stephen M. Batill, and Laura Carlson. "Modeling product form preference using Gestalt principles, semantic space, and Kansei." ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, 2012.

McBride, R. D., F. S. Zufryden. 1988. An Integer Programming Approach to the Optimal Product Line Selection Problem. *Marketing Science* **7**(2) 126-140.

McManus IC, Jones AL, Cottrell J. The aesthetics of color. Perception 1981;10:651–666.

Mollon, J. D. 1982. Color vision. *Annual Review of Psychology* **33** 41−85.

Nair, S. K., L. S. Thakur, K.-W. Wen. 1995. Near Optimal Solutions for Product Line Design and Selection: Beam Search Heuristics. *Management Science* **41**(5) 767-785.

Nagamachi, Mitsuo. "Kansei engineering: a new ergonomic consumer-oriented technology for product development."

International Journal of industrial ergonomics 15.1 (1995): 3-11.

Ou, L.-C., M. R. Luo, A. Woodcock, A. Wright. 2004. A Study of Colour Emotion and Colour Preference. Part I: Colour Emotions for Single Colours. *Color Research and Application* **29**(3) 232-240.

Ou, L.-C., M. R. Luo, A. Woodcock, A. Wright. 2004. A Study of Colour Emotion and Colour Preference. Part II: Colour Emotions for Two-Colour Combinations. *Color Research and Application* **29**(3) 292-298.

Page, A. L., H. F. Rosenbaum. 1984. Redesigning product lines with conjoint analysis: how Sunbeam does it. *Journal of Product Innovation Management* **4** 120-137.

Rossi, P. E., R. E. McCulloch, G. M. Allenby. 1996. The Value of Purchase History Data in Target Marketing. *Marketing Science* **15**(4) 321-40.

Schloss, K. B., Strauss, E. D. and Palmer, S. E. (2013), Object color preferences. Color Res. Appl., 38: 393–411.

Shi, L., S. Ólafsson, Q. Chen. 2001. An Optimization Framework for Product Design. Management Science 47(12) 1681-1692.

Simonson, I., A. Tversky. 1992. Choice in Context: Tradeoff Contrast and Extremeness Aversion. *Journal of Marketing Research* **29**(3) 281-295.

Smet, K., Ryckaert, W. R., Pointer, M. R., Deconinck, G. and Hanselaer, P. (2011), Colour appearance rating of familiar real objects. Color Res. Appl., 36: 192–200.

Terwogt MM, Hoeslma JB. Colors and emotions: Preferences and combinations. J Gen Psychol 2005;122:261–263.

Thurston, D. L. 1991. A Formal Method for Subjective Design Evaluation with Multiple Attributes. *Research in Engineering Design* **3**(2) 105–122.

Train, K., 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press.

Vanhemert, K., 2014, September, Apple Made a Perfect Watch, But Needs to Decide What It's Good For, *Wired Magazine*, Retrieved from www.wired.com.