경제학석사 학위논문

PROMOTING DIVERSITY IN MOTION PICTURE EXHIBITION:

A STUDY ON SCREEN REALLOCATION IN SOUTH KOREA'S MOVIE BOX OFFICE

상영 영화 다양성 촉진:

대한민국 영화 산업의 상영관 재분배에 대한 연구

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경제학과

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ABSTRACT

PROMOTING DIVERSITY IN MOTION PICTURE EXHIBITION: A STUDY ON SCREEN REALLOCATION IN SOUTH KOREA'S MOVIE BOX OFFICE

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How can reallocating screens differently to different movies on a weekly basis change the resulting attendance? In this paper, the Korean film industry is examined with a special focus on screen reallocation in order to encourage there to be a greater variety of films displayed during exhibition. The paper discusses various aspects of the movie industry in South Korea before delving into modeling and analyzing film demand by examining data collected from the year 2012. Using a logit model with movie fixed effects, this study estimates a demand function for movies based primarily on the number of screens allocated to a given movie per week. Also the identification for finding instrumental variables for the endogenous screen-count variable is explained. With a demand function estimated, it is then used in an attempt to show the possible, resulting market shares under different screen allocations, ones that could create a more equal distribution of screens over the top-20 films. Through new screen allocations, one might be able to induce more diversity into the exhibition process for movies at theaters so that consumers can have more options and the potential for greater satisfaction.

Keywords: movie demand, entertainment economics, logit model, discrete choice model, screen allocation, diversity

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INTRODUCTION

The movie industry is an exciting market. Every week, there are new movies released to the public to view, react, and critique. Each movie is unique, and each one has a special story to tell that resonates differently in accordance with different people's personal views and tastes. In this respect, the Korean box office is particularly vibrant, having quite a range of films with varying content and quality. On one hand, big-budget, Hollywood films, like the Transformers series, do well; and, on the other hand, simple Korean dramas, such as Architecture 101 (건축학개론), can also find similar success. It is a market where domestic films compete alongside international films in an almost equal-sided battle. This research examines South Korea's box office market, estimates a demand function using a logit model, and applies the outcome to a counterfactual study, one that demonstrates the possible market shares that could result under other screen-reallocating scenarios.

Motivation:

At the inception of this study, the motivation was to discover what would happen if the screen quota policy in South Korea were not in effect. What would the changes be, particularly in regards to the predicted share of Korean movies, if more screens were allocated to foreign films? However, after seeing that, in all likelihood, the contemporary screen quota policy has very little effect[1] on actual screen allocation, attendance, and revenue, the focus then shifted into investigating how other sorts of screen policies could affect the market. For instance, while South Korea has had success in creating a sustainable movie industry, this process also seems to have led to a relatively high degree of homogenization in the movies released. Recently, there have been a lot of Korean thrillers or crime movies, American action and sci-fi films, and also Japanese animation. But, on the other hand, there are certain genres such as, say, Korean comedy, American romance, or Japanese dramas that are generally not shown to any extent in theaters (Park, 2012). Of course, this is partly due to the actual

[1] The screen quota was estimated to not be binding for the 2012 box office data. This will be discussed more fully in the Industry Description section.

supply of movies, but there also seems to be some preference given to certain kinds of films during the screen-allocating decision of movie exhibitors.

It is common for the seasonal hit-movie to dominate theaters so much as to crowd out what-could-be enjoyable films. In recent years, American superhero movies and Korean crime-thrillers have been the smash-hits (Park, 2010) that take up a lot of screen space and theater time, particularly during the summers. In looking at the weekly allocation of films in the box office and seeing the strong tendency for just a few films to be given most of the resources and attention of the market, the subsequent lack of options to choose from could be a concern for the consumer. Some good films do not get the distribution that they deserve because of the promotion of just a few blockbusters that have a high probability of capturing most of the market. In this kind of environment, it can be a real nightmare to go through the trouble of going out to the theater only to discover upon arrival that there is no desirable movie showing or, likewise, to check a movie's listing online only to discover that it is playing one or two times a day at a single theater on the other side of Seoul. Overall, it seems that, in the case of South Korea, as the film industry has become more mature, there is a less diverse movie portfolio being released in theaters, causing the shortage of various types of movies because of the major studios wanting to capitalize on big blockbusters (Kim, 2012; Lee, 2012; Song, 2012).

In this spirit of questioning how to induce more diversity in the way of movies through some sort of intervention—perhaps, subsidization of the industry—it is the goal of this research paper to attempt to compute what kind of subsidy would have to be implemented to serve as an incentive for movies to be more uniformly distributed across theaters. This study will first start by forming a demand model of the South Korean, box office market. Thereafter, counterfactual analysis will be undertaken to show the model's prediction for the industry shares under different screen reallocation rules and the market loss resulting from the non-optimizing behavior of the industry. This loss would require subsidization, the amount of which would be calculated for each type of policy. Lastly, the efficiency of each policy will be compared and analyzed to offer an appropriate solution for how to induce more variety into the movie market.

Literature Review:

As far as the structure for estimating the demand model, this paper draws mostly from the studies by Berry (1994); Berry, Levinsohn, and Pakes (1995); Nevo (2000); and Nevo (2001). Being some of the most preeminent papers in industrial organization, these studies feature logit models regarding price competition and demonstrate ways by which one might estimate demand functions for a product in order to make some sort of argument about the activity in that market. For this present study, a key feature was inspired from the BLP model (Berry, Levinsohn, and Pakes, 1995). In dealing with demand in the car industry, they were faced with the issue of endogeneity in their model. To solve this problem, they revealed the efficacy of using the competitors' characteristics as instrumental variables for the price variable. In the case of Nevo (2000), his paper demonstrated more explicitly the method of estimating demand models through random-coefficient logit models. This specific model is especially useful in analyzing markets with differentiated products, such as movies. Likewise, in Nevo's 2001 paper about market power in the ready-to-eat cereal market, he demonstrated not only how to estimate a demand function but also how to derive a model for the supply side when the exact costs for each product are not fully known. He was able to calculate price-cost margins and compare those with different models of market behavior to see which one best matches in order to suggest what kind structure the market operates under.

As for the motion picture market, there have also been various studies over the years, as researchers have created several ways to try to predict the profitability of one movie or another. Past articles that have dealt with issues in Korean cinema, particularly the Korean screen quota system, include industrial reports from the Korean Film Council and papers by Kim (2000), Jin (2006), Choi (2007), and Yecies (2007). In regards to the general estimation of movie demand, one particularly well-written researcher would be Eliashberg, whose studies have appeared several times in the literature of entertainment economics. Examples of his work would be Sawhney and Eliashberg (1996); Eliashberg and Shugan (1997); and Eliashberg, Jonker, Sawhney, and Wierenga (2000). Other influential researchers could include Prag and Casavant (1994), De Vany and Wells (1997), and Einav (2007). A less prominent study by Chang and Ki (2005) was also consulted for this study. All of these studies have used different models to varying degrees of persuasion. While some of these various studies simply try simply to estimate movie demand based on certain observable factors such as genre or budget, other studies take a further step by deriving the demand function and then using it to answer a specific question in mind about the market. In the case of Einav (2007), he estimates movie demand with the purpose of showing the degree to which the market could expand to a greater audience, which makes his work particularly noteworthy. In dissecting the seasonality effect from other factors, he presents a convincing way to model movie demand as being related to its seasonality and its "innate" demand. He was able to estimate a market-expansion effect as well as a "decay effect," the decreasing strength of a movie's appeal while in the box office.[2] His demonstration of how to sidestep estimating the innate quality of movies through movie fixed effects and the efficacy of using weekly panel data was particularly insightful.

Differences:

Overall, previous research papers have been concerned mostly with the United States box office market, and there have been few, well-established studies on non-United States markets such as South Korea, one that is also dynamic. In this way, the scope of this present paper is one difference with previous literature. Particular ways in which it differs from Einav's 2007 study are in having the key variable be the weekly number of screens for a movie instead of its market share, in having slightly different model specifications (such as about the utility derived from the outside good), and also in having different instrumental variables. Whereas Einav used the total number of movies released as his instruments, in the case of this paper, the instrumental variables that were used here were the sum of the characteristics of a given movie's competitors. In this sense, this method harks back to the BLP paper, where they used similar instruments for the price of automobiles. Thus, this paper is a fusion of various features from past studies in order to construct a demand model of the South Korean box office and set up some analysis over the screen allocation of different movies.

[2] It is a point also studied by De Vany and Walls (1997).

INDUSTRY DESCRIPTION

The Korean Screen Quota System:

The Korean film industry has come a long ways over the years, from being a baby to becoming a full-fledged industry that can compete squarely against Hollywood and other foreign films in its own domestic market. The extent to which South Korea has been able to develop a robust movie industry is quite intriguing, especially in considering that other countries have tried to foster a supportive domestic film environment but with less success. To give an idea about the size of South Korea's output, according to the UNESCO Institute for Statistics, the country was ranked eleventh in producing the most number of films in the world on average between 2005 and 2009, about at the same level as Italy and the United Kingdom (UNESCO, 2013). Moreover, in comparing the domestic film shares across several countries, South Korea turns out to be well within the top ten countries for several years now, a group which also includes countries such as Japan, India, China, and—of course—the United States (Screen Digest, 2013).

Over the years, Korea has tried different types of policies—including trade barriers, government funding, and tax breaks—to actively foster a competitive film industry (Jin, 2006). A screen quota is a policy that restricts the number of foreign films that can be released within a country either by limiting their exhibition to a specific percentage of total screens or a specific amount of time available. There have been a few changes in South Korea's policy over the past fifty or so years. In the early 2000s, the screen quota policy had been designated so that a screen was required to guarantee room for domestic films for 146 days of the year. This was true until the year 2006, when the screen quota was slashed in half to 73 days from this initial 146 days. This was part of a larger easing of trade restrictions between South Korea and the United States (Choi, 2007; Yecies, 2007).

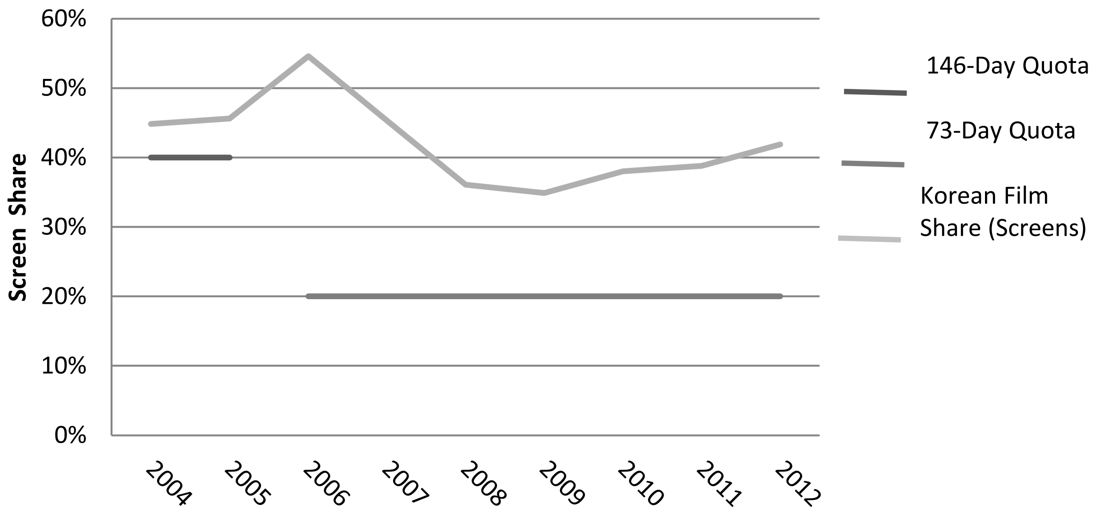
Incidentally, this halving of the quota policy coincided with big events in the film industry as well. In 2006, the Korean film industry was at a peak during that decade with a market share of 63.8% of total attendance. However, in the following year, the foreign market share caught up to the domestic share, and then between 2008 and 2010 foreign films surpassed Korean films (Park, 2012).

Some have termed this string of events following the policy change as an "industry crisis" (Park, 2008). However, the market recession should not be entirely attributed to the change in policy. The Korean Film Council's 2011 year review cited some other possible reasons behind this lackluster season in Korean movies. Namely, at that time, when more U.S.A. movies started to enter the market, this market shock coincided with a lack of good-quality, blockbuster Korean films and with an increase in the competition from out-of-theater (e.g. smart phones and illegal downloading) exhibition of movies (Park, 2011). Because of a reduction in the amount that the studios were investing in high-budget movies from 2007 to 2009 (Park, 2010), it seems that Korean film producers were being wary about the riskiness of the changing market, a move that would have affected the quality of the Korean films and their ability to attract an audience. Since this market disruption, there has been a recovery, first slowly in the years 2009 and 2010 and then more solidly thereafter. The gains in the domestic market share further suggest the robustness of Korean films with foreign competition.

The screen quota policy of allocating at least 73 days to Korea films can be interpreted as though the domestic share should be at least 20% of the total number of screens in Korea. In comparing this with the past historical domestic shares of the Korean box office, it would seem that it has been a long time since this supply constraint was binding. Figure 1 compares the estimated domestic share of total screens to the quota constraint for the years between 2004 and 21012. The graph[3] was estimated by summing the maximum number of screens allocated during a movie's exhibition, thus it does not take into account changes in the number of screens for a given movie over time. Using this calculation results in about an estimated 41.8% share of total screens to domestic films for the year 2012. This number is lower than what is actually observed in this paper's database, which was a share of 49.25% of total screens for domestic films. A possible explanation of this discrepancy is that using this technique perhaps gives the domestic films a downwardly biased estimate for its share of screens, because it does not take into account the longer lifespan of domestic films in the box office. However, because this was an expedient way to gather data for past years, this method was used to depict the past history of screen shares in the Korean box office.

[3] Using data obtained from the box office statistical website hosted by KOFIC.

FIGURE 1
Korean Screen Share and the Screen Quota



As can be since, this graph also indicates that the screen quota system has not been binding in several years, being as how Korean films were given more than enough screens for their allocation. This signifies the expectation of both distributors and exhibitors for the domestic audience to have a high demand for Korean films. Because of this, Korean films do not necessarily require support of a screen quota policy to artificially create demand for them.

If the screen quota system were to not have much of an impact, at least in recent years, then what is supporting the thrust of the South Korean movie industry? In some ways, it should not be too strange that Korean movies have been receiving more screens than the yearly stipulation. It could be that there are two points for South Korea's success in the motion picture industry. One is that the technical quality of South Korean movies has steadily increased to become comparable to that of Hollywood (Park, 2011; Kim, 2012). Secondly, Korean culture could be seen as being quite different from the Western culture as presented in Hollywood films, rendering Korean movies and foreign ones not so easily substitutable. What is meant by this is that they tell different stories and reflect different themes and messages. On one hand, Korean film companies have yet to make a significant super-hero movie, which is a regular staple of recent Hollywood production. On the other hand, Hollywood does not make films with the idea of *han* (한), a theme of long-suffering and injustice (Beech, 2002), which seems to be special to the spirit of the Korean people, as so often demonstrated in the "catastrophic narrative" of Korean cinema (Park, 2011). Thus, even if the quality between domestic and foreign products were huge, it could still be possible for low-quality, Korean films to obtain some share of the market. These two ideas of both quality and content indicate that what truly determines both the demand and the number of screen assigned to a movie is a given movie's expected appeal to an audience.

The Supply Side:

As for the supply side, it is assumed here that the aim of the exhibitors is to maximize profit; and consequently, it follows that one must assume that the presently observed allocation of screens is optimal according to the exhibitors' profit-maximizing constraints. These constraints could include the national screen quota policy, contracts with distributors, and also the costs and benefits of screening a movie.

Being as how this entertainment market does not exactly have effective prices, it is not clear what the between-film elasticities are in order to estimate substitution parameters, which would be useful in modeling the costs for theaters as Nevo (2001) did for the cereal market. However, instead of price, screens-count is similar to the concept of price for any other good in the way that the number of screens is related to the movie's public accessibility and in the way that it can reflect an expected valuation by distributors and exhibitors for a given movie. The screen-count is a kind of measure of market saturation or availability, for movies with high demand would occupy several screens as to offer a lower cost of access to the public. On the other hand, a movie less widely distributed can be considered to be more costly, as it cannot be reached as easily by as many people because of the increased transportation and opportunity costs.

The idea of market saturation would also imply that decreasing marginal returns to screen expansion exists for each movie; because as market saturation increases for a movie, the incremental gain the movie could receive in demand would conceivably not match the persisting costs of allocating an additional screen. Because this effect may be non-linear, it has some differences with a traditional pricing scheme. Theoretically, it would seem that theaters would display a film on a given screen as long as a certain percentage of the seating capacity is filled during each screening down to a threshold level, at which point it would switch the screen to another movie substitute or not show anything. In this way, opportunity costs exist for exhibitors to show a certain movie, since they must forego showing another movie on any occupied screen and forego getting the associated revenue.

Consumer Choice:

Defining the demand for movies is a tricky topic; because unlike apples and oranges, movies are quite heterogeneous as products in that no two are the same. Presumably, a given consumer will go see a movie every so often in a theater. While the penchant for seeing a movie in theaters could be influenced by the available bundle of films that are showing, it seems to be influenced a good degree by exogenous factors such as yearly seasonality in the short term and industrial trends (Einav, 2007) in the long term. In the case of South Korea, the yearly theater attendance per capita has been slowly increasing over the past decade with some recent fluctuation (Park, 2012). Once at the theater, the given consumer can choose the movie according to expected utility maximization, a decision that is based on the individual's preferences in conjunction with the movie's advertised image. What determines a movie's perceived appeal is a rather ambiguous concept. The way a movie is perceived depends on the consumer's knowledge of the product, which could differ greatly depending on the effects of word-of-mouth, advertisement, and the consumer's own expectation. According to Eliashberg, Jonker, Sawhney, and Wierenga (2000), a movie's perceived quality is related to the interactions between six kinds of consumers (e.g. positive and negative influencers and considerers) and their behavior of communicating to each other about the movie. The study discussed a model to predict the market share of an individual movie by gathering data from a pre-release screening to a test audience. As demonstrated in this study, before a consumer sees a movie, the decision-making process can be misguided by imperfect information stemming from perception and word-of-mouth interactions.

This is where using movie reviews as a predictor of a consumer's likelihood to select a particular movie is problematic for movie quality. Indeed, there are numerous movie reviews and ways to rate a movie on different scales from several movie-rating websites. However, movie ratings are *ex-post* to a consumer's viewing of a movie, and they do not necessarily reflect perfectly the preconceptions of the consumer that led to the actual movie selection. Oftentimes, some movies that are praised as being "high quality" do poorly in the box office, and this demonstrates the unreliability of using movie ratings as a measure for the quality of a movie to being viewed in a theater.

The Demand Side:

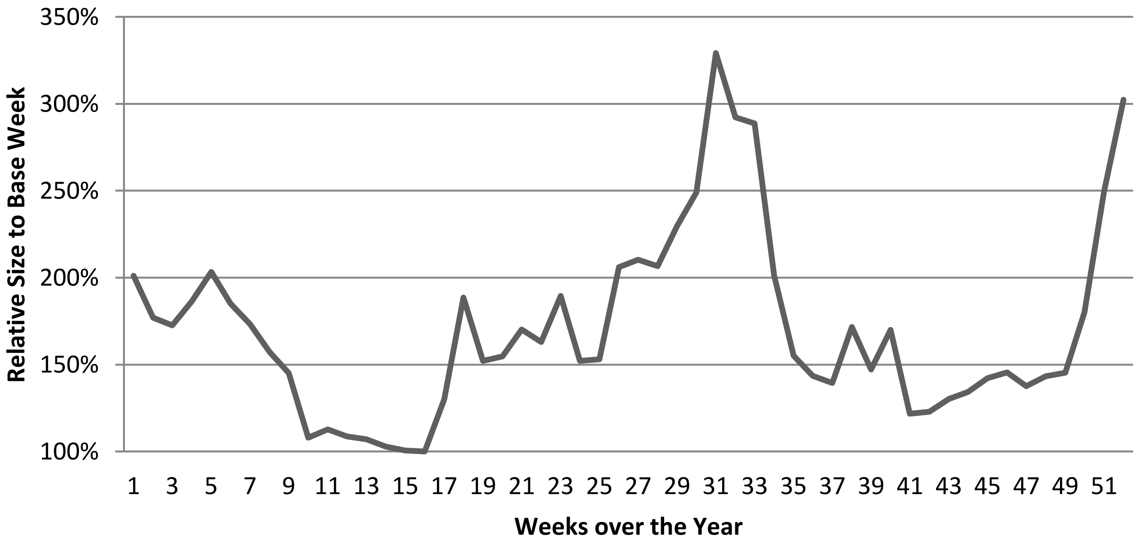
As described to some extent earlier, a part of movie demand is the movie's innate quality that appropriates its chance of success. This is not quite the same as the movie's creative quality; instead, it is about whether or not it is a film that would appeal to a mass audience when seen in a theater. Of course, there are many exhibition outlets nowadays—home TV, online web-videos, smart phones—that can be outlets through which to watch a movie. But, it seems as though certain movies do better in a given venue, particularly the big-screen theater, versus another. Thus, creative quality and theater-appropriate quality overlap, but they are not necessarily the same.

Perhaps the next most important factor in estimating the demand of a movie is its weekly number of screens. Whereas Einav (2007) used the internal market share of a movie, this study is concerned with screen allocation, and so screens-count is a better variable for this purpose. In Einav's study, the innate movie quality and the timing of a movie's release were basically the only two variables that the firms could directly control for, but adding screen-count allows for another factor that firms can control during profit maximization, which adds to the appeal of modeling movie demand in this way. There is a problem, however, with putting screen-count into the model, because it is endogenous and is correlated with the unobserved factors of the error term, and so instrumental variables will become a necessity. In determining the number of screens for a movie, a distributor must have some sort of idea about the movie's quality, which is derived from its content, story, director, actor, and numerous other factors. In finding instrumental variables for the screen-count variable, one should consider what factors distributors face in setting the number of screens. Nevertheless, the screen-count variable can be thought of as the firm's key choice variable.

Movies, also, show a kind of "decay"[4] in appeal over time, as expounded on by Einav's 2007 study. In being released for exhibition, a movie acts much like the concept of capital in macroeconomics: it has a limited lifespan in theaters. The nationwide audience gradually loses interest in the movie each week, and fewer and fewer people exist who would want to see it, as the movie saturates its potential market. In this way, it was observed in this paper's dataset that usually the most number of screens were given to a movie in its opening week, and thereafter screens were slowly subtracted from this number, reflecting the diminishing public interest.

Finally, there is quite a bit of seasonality in the box office market. Figure 2 shows the average, historical box office total per week, which is adjusted for yearly industry growth and the two major holiday seasons in Korea, the Chinese New Year (설날) and the Fall Harvest Festival (추석).

FIGURE 2
Seasonality in the Korean Box Office



Here, the graph is set in terms of percentage points with week 16 being the base week with it being, on average, the lowest point of the year. As can be seen, during both school semesters, approximately in weeks 9 – 24 and in weeks 35 – 49, the box office total decreases a lot. The in-semester increase in

[4] "Depreciation" is perhaps a better term, because the audience loses "appreciation" for the movie.

May (about weeks 18 – 21) could be attributed a series of 1-day holidays in South Korea, such as Children's Day, Parent's Day, and Buddha's Birthday, during which families often spend the time together.

In summary of what to consider for movie demand, there are four aspects—quality, screen allocation, movie depreciation, and seasonality—that are the major parameters to be estimated in forming a demand function, as reflected in Equation 1.

$$(1) \qquad f(x) = \begin{bmatrix} movie\ quality, \\ screen\ allocation, \\ depreciation, \\ seasonality. \end{bmatrix}$$

DATA COLLECTION

Variable Discussion:

Chang and Ki (2005) provided a good listing of observable characteristics of films for which data could be collected. Particularly, the paper's recommendation of using an actor's past history to predict the current movie's sales seemed like a reasonable idea. Data was collected with the following information: a movie's name, release date, per-week attendance, per-week screen count, and some additional information about each movie's actor, director, and production company. Also, a few variables were calculated from the collected data, namely a movie's age in the box office (that is, how much time has passed since its release), the weekly share of a movie, and the strength of the competition, as will be explained shortly.

Because movies continually change in the box office in terms of entering and exiting the box office as well as an individual movie's strength of appeal and availability, a timeline based on the week seems to best reflect this constantly changing arena. This seemed more appropriate than yearly data, as it allows for the flexibility of panel data. Moreover, in yearly data, the variation observed across weekly changes is not shown. In comparison with daily data, weekly data also seems better, because it is simpler and less time-consuming to collect. For each observation, there are nine variables about the observed characteristics of the movies that were collected and used.

ATTENDANCE. The movie's weekly attendance will be the dependent variable that the logit model will try to estimate. Even though data on weekly revenue is also available, attendance better reflects the individual, consumer preferences, because it is not distorted by the pricing scheme.[5] From this weekly attendance data, the weekly movie share was calculated, and the logit-ratio could be formed.

RELEASE DATE. As a movie ages in the box office week by week, it experiences diminishing sales. Subsequently, the release date is taken into consideration largely for defining the time since a movie's release. This in turn helps calculate the "decay" effect, as also studied by Einav in his 2007 paper.

SCREEN COUNT. This is a variable that denotes the number of screens for a given movie in a given week. In general, this represents the relative availability of the film across the national market; or, in other words, the market diffusion of the product. One should expect this to have a significant, positive impact on a film's market share. However, logically, there seems to be a natural limit to how many viewers an exhibitor can attract into the audience by adding an additional screen. At some point, the target market must become saturated. In reflection of the diminishing returns to adding another screen to a movie's allocation, the log of the movie's weekly number of screens is taken, which should also better help the interpretation of the estimated coefficient of this variable in the logit model.

MOVIE CHARACTERISTICS. For each movie, there is a grouping of six variables to be referred to as the movie's "characteristics." For the movie's characteristics, the goal is measure the movie's production experience and potential appeal. Following the suggestion of Chang and Ki (2005), information about every director's, actor's, and production company's past films were

[5] Prices are generally uniform across the available selection of movies, especially for the within-theater selection. Also, the consumer will usually be faced with the same prices for a movie between theaters. Thus, prices are not an important factor in this choice model and can be ignored. Movies with high ticket prices could be associated with 3D films or other special exhibitions. From this present study's own dataset, it was deduced that the average ticket price of 2012 was ₩7,380 KRW, which seems appropriate as most tickets these days seem to be about ₩7,000 or ₩8,000 KRW ($7 or $8).

obtained. For each of these three entities, the goal was to find (1) the total number of films produced and also (2) the box office revenue in South Korea for the last film made by that entity. So stated simply, there are two variables denoting the movie director's total number of produced films up to that point in time and also the financial success of the director's last film in the Korean box office. The same kind of information was gathered for the actor and production company as well. These were perhaps the most important variables of this study, because it is from this group of six variables that one can construct the instrumental variables, which were calculated by summing each of the competitors' six movie characteristics. This allows each observation to have its own measure of the strength of the competition that it faces in that week. Later on, the reasoning for the identification of these as the instrumental variables will be explained in more detail.

Several other descriptive variables were consider but ultimately not used because of either lack of data or lack of usefulness. Other data that was gathered but not used included factors such as weekly revenue, seating capacity, box office ranking, genre, age-appropriate rating, and several others. Indeed, much of this could be found through KOFIC's online websites and also through IMDB.com. It is not necessarily hard to think of descriptive information of a movie (i.e. what kind of camera was used during production), instead the tricky part is in finding that data for all of the movies and observations. Indeed, if this study could have had the movies' production budget, that would a have been a great boon, but that data was only found for the American movies and not the Korean movies, thus this variable was dropped.

Sources:

The data that was used in this study has been obtained primarily from a box office data site that is hosted by KOFIC. A really useful site, it has a lot of fairly detailed data regarding the Korean box office including daily, weekly, and monthly revenue, attendance, screen count, and seating capacity for each film shown, as well as this same data specified according to each theater in different cities, creating an impressive data reserve. Categorical information was retrieved from KOFIC's annual industry report for 2012 as well as the English version of KOFIC's industry directory for information regarding the actors and directors. In this way, KOFIC supplied practically all of the data used in this study.

Table 2 gives an idea for what kind of movie industry data can be obtained and from where. For example, age-appropriate ratings were obtained from the Korea Media Rating Board, and other data was initially gathered from such websites as IMDB.com and BoxOfficeMojo.com. However, for this study, most of this can be disregarded as most of this data ended up unused.

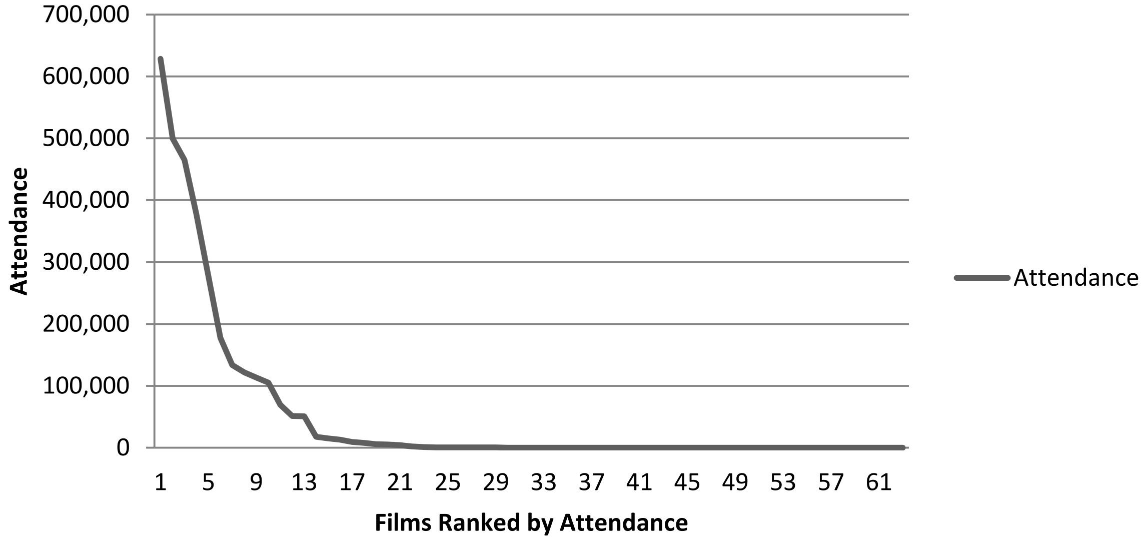
TABLE 1 **Data Sources**

KOFIC Korean Cinema 2012 Report	movie names, runtime, production camera, Korean director, Korean actor, Korean production company, genre, animation, type of screenplay
KOFIC Online Database	release date, revenue, attendance, number of screens, screenings, country of origin, seating capacity, box office ranking
Korean Movie Ratings Board	Korean movie ratings
BoxOfficeMojo.com	other country statistics
IMDB.com	USA movie budgets, foreign director, foreign actor, foreign production company, genre, animation, originality

Data Selection:

The South Korean movie market seems to be highly concentrated in such a way that the top five movies, thereabouts, obtain most of the share of revenue. The movies below the top-10 have very little earnings, and the ones below the top-20 are very obscure films. However, in one week, as many as 50 to 80 films can be shown in theaters, resulting in a “long-tail effect” in the earnings curve. Figure 3 shows a snippet of what a typical week in South Korea’s box office could look like. Here, it is represented by the third week of 2012. The movies are ranked in terms of attendance from largest to smallest, and a very long “tail” is clearly recognizable starting at about the seventh ranked film.

FIGURE 3
Example of the Long-Tail Effect: Week 3, 2012



With this "long-tail" effect in mind, instead of taking data from every movie released in South Korea, data was collected only for the movies in the top-twenty for the Korean box office during the year 2012. The left-out films are assumed to be part of the "other good" in the outside market. According to this rule-of-thumb, this should have created 1,040 entries for the 52 weeks of the year, but a few films in the top-twenty were dropped (e.g. reruns of old, 1970s movies), and a few more from below the twentieth ranking were added in (such as the extended exhibition of Mission Impossible and other popular films in that year). The total number of observations turned out to be 1,092 for an average of 21 movies per week. It was according to these conditions for selection that the dataset was collected.

Summary Statistics:

A database was collected and compiled with observations from 226 different movies that were released for exhibition within South Korea in the year 2012. The data was set in terms of the Korean currency, the *won*, for that year. In Table 1, one can see the summary statistics for the dataset, including the means, standard deviations, minimums, and maximums. As can be seen, the database features a large range.

TABLE 2 **Descriptive Statistics of Variables**

KEY VARIABLES	Mean	Standard Deviation	Minimum	Maximum
Attendance	172,513	370,674	208	4,017,061
Screens	210	210	1	1,210
Screenings	4,012	5,621	1	36,056
Time Relative to Release (in weeks)	3	5	-9	48
COMPETITION'S CHARACTERISTICS				
Director 1 (number of movies)	134	49	45	281
Director 2 (in 2012 KRW)	₩102 billion	₩34.6 billion	₩12 billion	₩179 billion
Actor 1 (number of movies)	564	151	235	906
Actor 2 (in 2012 KRW)	₩141 billion	₩55 billion	₩30.7 billion	₩271 billion
Production 1 (number of movies)	512	135	208	771
Production 2 (in 2012 KRW)	₩93.9 billion	₩34.8 billion	₩6.33 billion	₩174 billion
Number of Observations: 1092				

To clarify, in the section for the competition's characteristic variables, the first variable (1) corresponds to the number of movies made by that entity in his or her career. For example, *Director 1* would indicate the number of movies produced in the past by that movie's director. An example of which could be The Hobbit movie, which came out at the end of the year, and its director was Peter

Jackson who had done however many films before releasing that film. However, the numbers that are displayed in Table 1 are the *sums* of a given movie's competitors, meaning if one were to divide these numbers by 20 then that would result in—for reference— approximately the average number of films per entity. So, the average director had six or seven movies in his portfolio before releasing a movie in 2012. As can be seen, on average, actors and production companies have a much greater portfolio or more experience in making movies than directors, interestingly enough. Next, the second variable (2) corresponds with the amount of revenue received by that entity's last film as released in Korea. Again, the numbers that are presented in the table are the sums of the competitors. In some cases, the entity had not previously released a movie in Korea, so a zero was registered for that observation. It is in these two terms for three different entities that the strength of a movie's own competition is measured.

Also, the variable, *Time Relative to Release*, refers to the current movie's week relative to when it was officially released. This number is in terms of weeks, and it might sometimes be negative, as seen in the table. When this is true, it would indicate a pre-release screening of the movie, perhaps a special screening to gauge an audience's reaction to the movie beforehand. Usually this happened within a month before a movie's official release, but the earliest in advance was nine weeks prior to its release.

THE MODEL

The Logit Model:

To calculate a movie demand function, a logit model will be derived and utilized. To start off, one can formulate a utility equation from the previously theorized attributes of movie demand. In particular, for the later analysis, one would need to include the screen-count variable into the demand function. So, using notation similar to Einav (2007), the utility function of the consumer takes the following form:

$$(2) \qquad u_{ijt} = \theta_j + \lambda(t - r_j) + \Lambda(t - r_j)^2 + \sigma \log(n_{jt}) + \tau_t + \xi_{jt} + \varepsilon_{ijt},$$

where there are three subscripts $\boldsymbol{i}$, $\boldsymbol{j}$, and $\boldsymbol{t}$, meaning consumer $\boldsymbol{i}$ can see movie $\boldsymbol{j}$ in week $\boldsymbol{t}$. The innate movie quality is set as $\boldsymbol{\theta_j}$, which will be calculated through movie fixed effects. The time term, $\boldsymbol{t - r_j}$, with $\boldsymbol{r_j}$ standing for movie $\boldsymbol{j}$'s official release week, shows how many weeks have passed since the film has been released, and $\boldsymbol{\lambda}$ is the depreciation effect of a movie's earnings in the box office. It is assumed that this depreciation effect is a non-linear effect, as is reflected by the squared term with the coefficient, $\boldsymbol{\Lambda}$. The weekly assigned number of screens for movie $\boldsymbol{j}$ is given by $\boldsymbol{n_{jt}}$, and $\boldsymbol{\sigma}$ is its effect after taking the log. The time fixed effects are included in the term $\boldsymbol{\tau}$. In the case of this study, months were used for time fixed effects, but weeks could perhaps be just as effective for databases with several years of observations. The term, $\boldsymbol{\xi_{jt}}$, represents movie-time specific shocks to demand which cannot be explained by the movie fixed effects, the decay pattern, the number of screens, or the time effects. This term will become the residual of the econometric model.

Since these unobserved factors might affect the exhibitor's decision in allocating the number of screens to a movie in any given week, the number of screens, $\boldsymbol{n_{jt}}$, is endogenous. One note, however, is that any component of unobserved movie quality, which is fixed across time, is controlled for by $\boldsymbol{\theta_j}$ and is, therefore, excluded from the error term. The identification for the instrumental variables for $\boldsymbol{n_{jt}}$ will be discussed below.

The outside good's utility is assumed to be the following:

$$(3) \qquad \boldsymbol{u_{i0t} = \varepsilon_{ijt}},$$

which might not be the best assumption because of its simplicity. There could be a more accurate specification for how the outside good varies with time, unobserved characteristics, shifts in preference for leisurely outings, technology, or entertainment, and this chosen simplification is somewhat different than in some other movie demand studies. It is assumed that $\boldsymbol{\varepsilon_{ijt}}$ has a type I extreme value distribution, which is independently and identically distributed across consumers, films, and time periods.

This gives us the standard logit form for the probability that a consumer will choose movie j[6]:

[6] Since consumers do not differ with respect to any observable variables, the individual choice probability is also the expected market share.

$$(4) \qquad \boldsymbol{s_{jt}} = \frac{\exp\left(\theta_j+\lambda(t-r_j)+\Lambda(t-r_j)^2+\sigma\log(n_{jt})+\tau_t+\xi_{jt}\right)}{1+D_t},$$

where $\boldsymbol{D_t}$ is the market demand at period $\boldsymbol{t}$.

$$(5) \qquad \boldsymbol{D_t} = \sum_{k\in J_t} \exp\left(\theta_k + \lambda(t-r_k) + \Lambda(t-r_k)^2 + \sigma\log(n_{kt}) + \tau_t + \xi_{jt}\right).$$

Thus, one can obtain the linear form[7] of the model as the following:

$$(6) \qquad \log(s_{jt}) - \log(s_{0t}) =$$

$$\log\frac{s_{jt}}{s_{0t}} = \theta_j + \lambda(t-r_j) + \Lambda(t-r_j)^2 + \sigma\log(n_{jt}) + \tau_t + \xi_{jt}.$$

With this model, there is one key assumption: that the residuals, $\boldsymbol{\xi_{jt}}$, are orthogonal to the exogenous, explanatory variables. However, the screen-count variable is probably not exogenous, as discussed above; therefore, one needs to find instrumental variables for $\boldsymbol{n_{jt}}$.

To summarize the equations here, there are just a few variables used to compute this model: number of screens, time effects, movie effects, and then a term for the time relative a given movie's release. Of course, because of the dummies variables in the two fixed-effects groups, one from each group will be dropped to avoid perfect collinearity.

Identification:

With the number of screens, *n*, being correlated with the error term, the question becomes why should one use the movie characteristics of the competition as instrumental variables for a movie's screen allocation? In order to identify proper instrumental variables for screen-count, this study's approach is similar to that used in the classic BLP model, and similar logic dictates why these chosen instrumental variables would work well.

Distributors and exhibitors can see a signal in the week-specific, unobserved characteristics of each movie that indicates to them how many screens to allocate to each film. Also, the characteristics of a movie's competitors are correlated with a firm's decision in allocating screens to a movie. The reason is that, given the quality of the movie (observed and unobserved), stronger competition means

[7] One can refer to Berry's 1994 paper to see more clearly how to derive the market share equation from the utility equation.

that exhibitors will find it optimal to allocate fewer screens to a given movie. This is analogous to the reasoning used to justify Berry, Levinsohn and Pakes's (1995) use of product characteristics of competing products as markup shifters and, therefore, instruments for price.

Furthermore, it is also assumed that the characteristics of competitors are orthogonal to the unobserved characteristics of a given movie, which appear in the residuals of the model’s error term. That is, the week-specific demand shocks of a movie are assumed to be uncorrelated with the previous performance of the directors, actors and production companies involved in the other movies showing during the same week. If the model did not include movie fixed effects, this assumption would be harder to make, since the release timing of a movie, and therefore the identity of its competitors, would depend on its unobservable characteristics. However, it is assumed that the week-specific demand shocks were not known at the time that the release date decision was made.

Thus, because the strength of the competition is correlated with the screen-allocation decision and is orthogonal to a movie’s unobserved characteristics, the characteristics (the director’s, actor’s, and production company’s past history) of the competing films will be used as the instrumental variables for screen count in this model.

The Outside Market:

In the case of Einav (2007), he estimated the outside market as being, in essence, the total attendance subtracted from the estimated country population during each week. He also had another specification for the utility of the outside product, which is different from this study’s assumption. Because of this difference with the outside good’s utility, another route was taken to estimate the outside market share.

To calculate the outside market, firstly historical data on the overall box office aggregate data were gathered for the years 2004 to 2012. Because of the fluctuation in the expansion and contraction of the industry, the ratios of these aggregates were used to inflate and deflate the weekly market size for each week (1 to 52) in each year between 2004 and 2012 to be adjusted relative to the base year.

Lastly, the overall market size[8] was computed by taking the maximum value across those years and then adding an additional ten percent**.** Thus, the share of the "outside good" is computed as being the amount of the total market size leftover once the sum of the shares of the weekly movies is subtracted out.

RESULTS

Estimated Parameters:

Using the computer program, STATA, to run this basic model with the gathered data, the resulting output that is generated is displayed in Table 3. Both the instrumental variable regressions and the basic ordinary least squares regressions are included for the sake of comparison. Each one of these eight different regressions features 1,092 observations for 226 films.

Firstly, each estimated coefficient—namely, the one for the movie's screen-count and the two for the decay effect—come out strongly significant in each model and with very low standard deviations. Each sign of the coefficients seems reasonable: positive for the screen-count and negative for first decay effect. The squared decay effect, Λ, comes out as being positive, suggesting that the decay is marginally decreasing in its effect. But with an estimated parameter of 0.005, this positive pull is barely noticeable.

As hoped for, with the instrumental variable regressions, each of the estimated *sigmas* is lower than their counterparts estimated through the ordinary least squares regressions. In some cases, these estimated coefficients are much smaller relatively. In each case, except for one, the *sigma* is

[8] Actually, the total attendance was inferred from the total revenue for each year because of not having data on yearly attendance and having yearly revenue instead. To translate the market size from revenue into attendance, the following ratio was used

$$m_t = \frac{M_t}{\sum_{j \in J_t} r_{jt}} * \sum_{j \in J_t} a_{jt},$$

where m is the total market size in terms of attendance per week t, M is the market size in terms of revenue per week, a is the attendance count for movie j in week t, and r is the amount of revenue for a movie in one week. Basically, weekly attendance is summed up and then inflated based on the ratio of weekly revenue to market size in terms of revenue.

estimated as being less than 1, with the benchmark model being 0.94, a number really close to 1. This is an interesting result, which implies that attendance should increase by almost the same percentage change as the change in screen-count for any given movie. So, if one were increase the number of screens for a certain movie by 100%, keeping other factors constant, a 94% increase in attendance should be likewise expected. With these results, it looks like the instrumental variables have worked well in reducing the endogeneity bias. In comparing each of the fixed effects, the movie fixed effects make a big difference for both types of regressions, causing a dramatic increase in the magnitude of the decay effect and a general lowering of the screen-count effect.

TABLE 3 **Estimated Results**

	Without F.E.	With Time F.E.	With Movie F.E.	With Movie & Time F.E.
I.V. REGRESSION				
λ	**-0.095** (0.014)	**-0.102** (0.013)	**-0.287** (0.028)	**-0.252** (0.032)
Λ	**0.002** (0.001)	**0.003** (0.0005)	**0.006** (0.0005)	**0.005** (0.0004)
σ	**0.881** (0.192)	**1.022** (0.167)	**0.777** (0.181)	**0.948** (0.152)
O.L.S. REGRESSION				
λ	**-0.103** (0.0155)	**-0.107** (0.014)	**-0.248** (0.019)	**-0.228** (0.0302)
Λ	**0.003** (0.0004)	**0.003** (0.0004)	**0.005** (0.0004)	**0.005** (0.0004)
σ	**1.202** (0.023)	**1.212** (0.022)	**1.143** (0.024)	**1.147** (0.023)
$\mathbf{R^2}$	0.748	0.79	0.8742	0.8892

One of the concerns discussed in this study was the lack of a good way to estimate the innate quality of a film. As described earlier, to deal with this, movie fixed effects was employed, greatly helping the estimation process. Yet, for further investigation, one could run a regression with the actual movie characteristics (its genre, rating, runtime, etc.) on the movie fixed effects coefficients that were calculated in estimating the logit model (Einav, 2007). When such a process was attempted with this paper's own dataset, the ordinary least squares regression resulted in a fairly low R-square, meaning that, if one were to utilizes these observable characteristics in the benchmark model instead of the fixed effects, it would account for very little of the innate quality of the movies. Therefore, it is a sign that using movie fixed effects truly does a better job in capturing movie quality than trying to use observable movie characteristics as predictors.

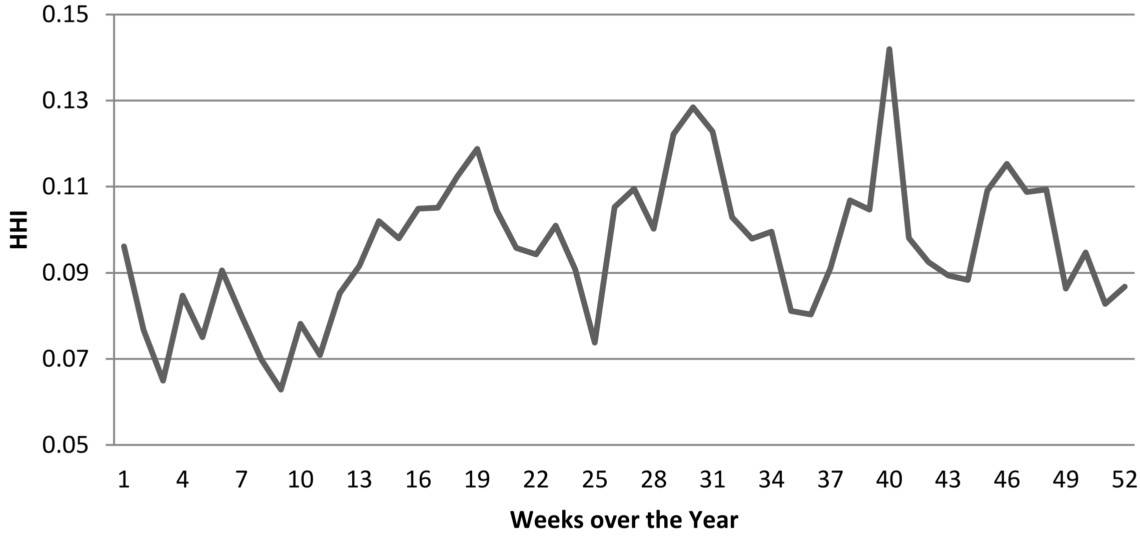
SCREEN REALLOCATION

Evidence of Screen Concentration:

Having established a demand model for movies based on screen-count, one can use this to analyze screen policies and the issue of movie diversity during exhibition. To clarify how much of a problem the lack of variety is, one can look again at the "long-tail" phenomenon, a reoccurring theme in the entertainment industry where the market is dominated by only the few top movies. For example, using the data in this study of the South Korean market, the top 4 or 5 films—the ones that are given the most screens for exhibition—take on average of between 76% and 83% of the weekly earnings, even though there could be as many as 60 films in that week. This creates something like a "winner-take-all" scenario that reinforces the tendency for exhibitors to give lots of screens to a few, valuable films instead of equally distributing them out.

Another indication of the amount of diversity in movie exhibition is the Herfindahl-Hirschman index. With this index, one can compute a measure of the amount of screen concentration for each week. Figure 4 shows the changes of this index over the course of the year in 2012 to give an idea of how competitive the box office changes over the year.

FIGURE 4
Weekly HHI for Screen Concentration (2012)



It shows that the HHI index usually ranges between 0.06 (fairly competitive) to 0.14 (moderately concentrated) throughout the year. Ultimately, this study will compare the different policies' ratios of the average change in HHI with the change in movie attendance to show what could be the most efficient policy of reducing screen concentration while minimizing the audience loss that results from an allocation of screens across movies that does not maximize attendance.

Screen Policies:

Having established a demand model that is based on the movie's screen-count, one can predict the market effects on a number of diversity-inducing policies that are based on solely screen allocation. In this study, six different policies will be presented and suggested as ideas of conditions of constraint to manipulate exhibition. Each one has a different way of reshuffling the screens between the weekly movies so as to keep the total number of screens the same as to what is observed. Each policy is concerned only with the top 20 films, and each will be explained and examined here.

The first policy, *a change of 75*, is where films in the top-10 (by screen count) have 75 of their screens subtracted, and the films ranked from 11 to 20 have the 75 screens added to each one of them. So, in other words, 750 screens are subtracted from the top-10 films and given to the bottom-10 films. The second film policy, *a change of 20*, is very similar; except, that instead of 75 screens being subtracted and added, the number is reduced to 20 screens for a more moderate change.

The third policy, *a linear change*, is a transformation that follows the equation:

$$(7) \qquad S_{NEW} = \begin{cases} S_{OLD} + \big((RANK - 11) * 5\big), & 1 \leq RANK \leq 10 \\ S_{OLD} + \big((RANK - 10) * 5\big), & 11 \leq RANK \leq 20 \end{cases},$$

where S is the number of screens for a movie and where $RANK$ is the film's ranking in terms of number of screens. It can be verified that in ranks 1 – 10 a constantly decreasing amount is subtracted from the original screen count and that for the eleventh ranked movie this transformation becomes a positive addition instead of a subtraction. So, once again, the top-10 films lose a total of 275 screens, while the bottom-10 films gain a total of 275 screens. The unique aspect of this policy is simply that the magnitude of the adjustment is weighted by the relative rank of each film, where the greatest change per film is an addition or subtraction of 50 screens and the smallest is of 5 screens.

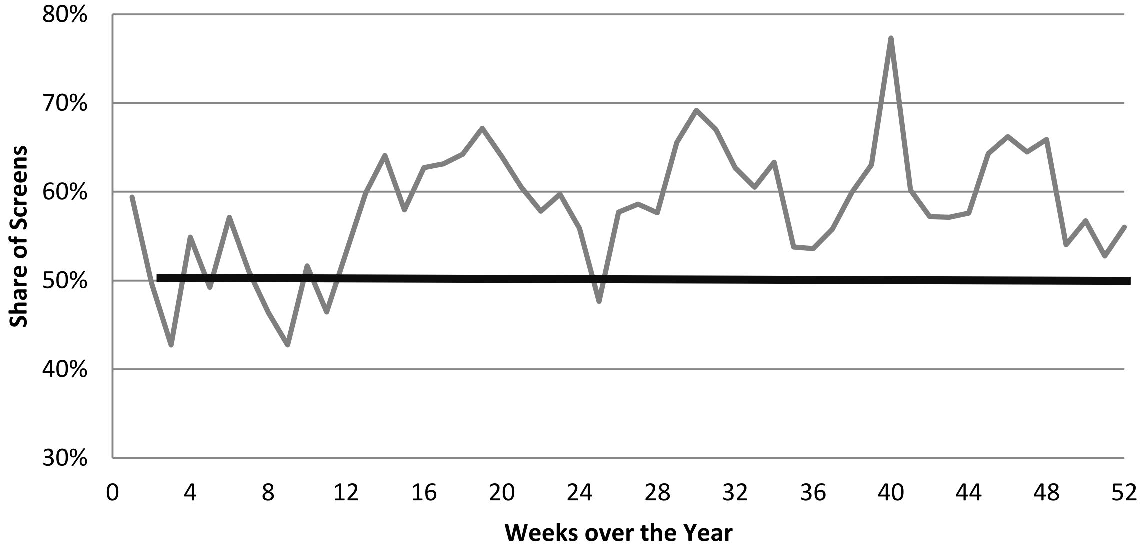
The fourth policy, *a discontinuous change*, is like the previously described one in that it is a weighted transformation with respect to ranking; however, this new function is discontinuous, and instead of giving more weight to ranks 18, 19, and 20 in the bottom-10 films, it gives it to ranks 11, 12 and 13, for example. Like the previous allocation rule, the top-10 movies lose the same amount of screens in the same way. Its reallocation function is the following:

$$(8) \qquad S_{NEW} = \begin{cases} S_{OLD} + \big((RANK - 11) * 5\big), \\ \hfill 1 \leq RANK \leq 10 \\ S_{OLD} + (50 - (RANK - 11) * 5), \\ \hfill 11 \leq RANK \leq 20 \end{cases}.$$

Here, it can be verified that Equation 8 puts more emphasis on the higher-ranking, bottom-10 films rather than the lowest ranked ones, which is contrary to the previous policy.

For the last two screen allocation policies, they both rely on defining the collective screen share of the top-5 films. Therefore, Figure 5 is presented to depict how the share of screens for the top-5 films changed over the course of 2012. This chart closely mirrors the previous one that shows the changes in the Herfindahl-Hirschman index for screen concentration.

FIGURE 5
Share of Screens of the Top-5 Films

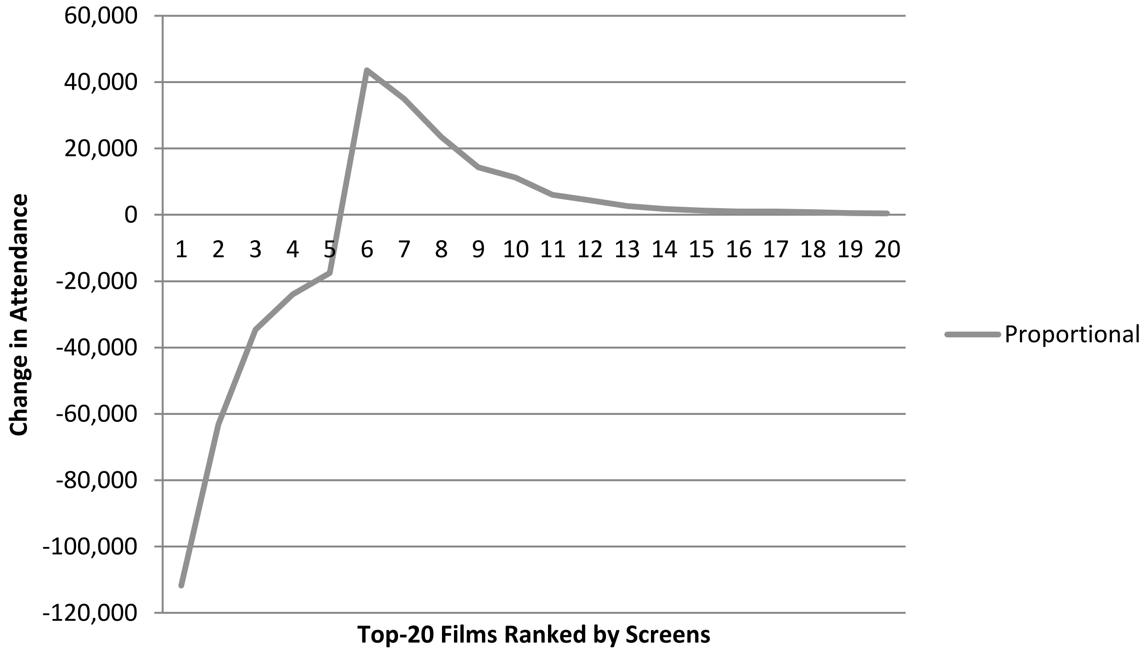


With this in mind, the fifth policy, *a proportional change*, is one where the sum of the screens included in the top-5 films can be no more than 50% of that week's total. If this constraint is not met, then each one of the top-5 films has screens subtracted in relative proportional to their market share until their sum is below the halfway mark. These subtracted screens are then added in relative proportion to the bottom-15 films until they are totally redistributed out. As could be seen in the previous graph, there are only a few weeks in the year where the share of this group of films is actually lower than the target constraint. This took place rather early in the year when screens were actually not highly concentrated. In the event that the top-5 films possess less than 50% of the screens, then nothing is changed in that week's screen allocation.

The last and sixth policy, *a biased change*, is one that is similar the fifth policy. Also in this one, the top-5 movies are limited to hold no more than 50% of the total number of screens for that week. To make this work, the excess number of screens are subtracting in relative proportion from the top-5 films (exactly like in fifth policy); but this time instead of giving the screens in proportion to the bottom-15 films, they are given first to the films with the most screens already of the bottom-15 so that each movie's screen-count is no more than that of the fifth ranked movie. The subtracted movies are thus redistributed to ranks 6, 7, 8, and so forth until all screens are redistributed out. But, once again, the key here is that the bottom-15 films' screen-count can equal the fifth rank but cannot exceed that number. Usually, for this policy, it was found that most of the subtracted screens were entirely redistributed into ranks 6 to 10, thereabouts.

With those rules in mind, the new screen allocation for each policy for each of the fifty-two weeks was calculated. This new, counterfactual data is plugged into the benchmark model to predict the shares of attendance for each movie during each week. The change in attendance from the observed data to the counterfactual estimates is then compiled for each policy. For simplicity, one example of the results from the hypothetical policies is displayed in Figure 6, while other graphs in the appendix section have a complete depiction, showing the results of each policy. Figure 6 shows the average changes in attendance for the *proportional-change* policy. As shown, the policy predicts a subtraction of 20,000 to 110,000 viewers from the top-5 movies and an addition of 10,000 to 40,000 viewers for ranks 6 through 10.

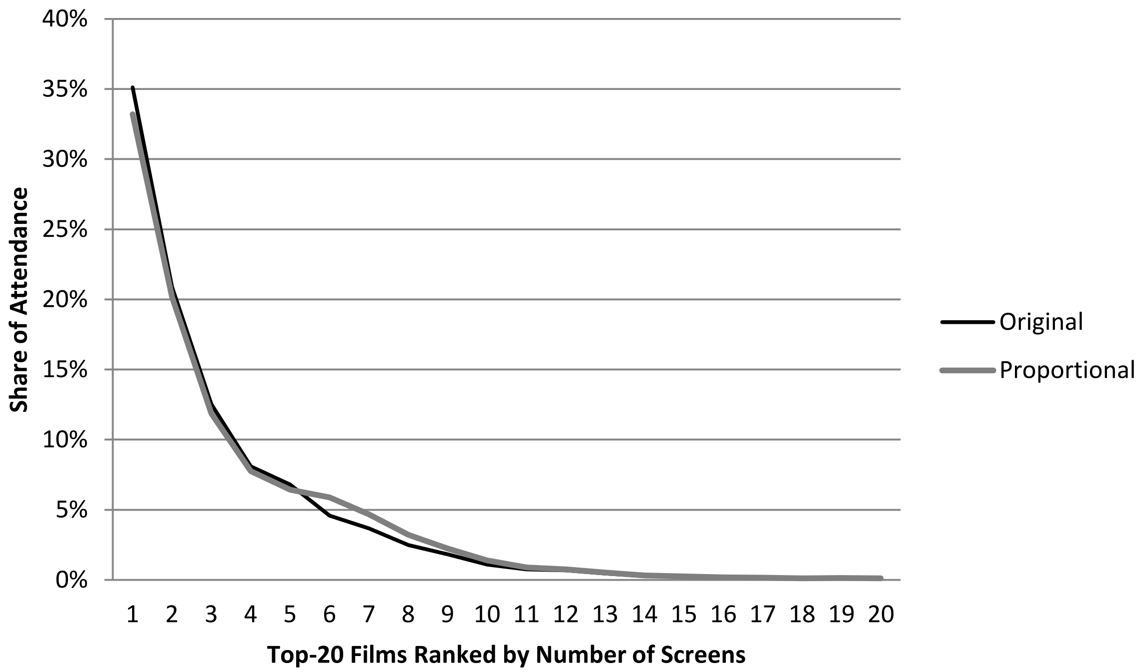
FIGURE 6
Average Change in Attendance for the *Proportional Policy*



The results imply an overall net loss of attendance because of the new screen reallocation. This is reasonable; because the assumption is that the current allocation maximizes revenue and attendance. As for the other policies, they similarly predict a redistribution of the audience attendees from the top films toward the bottom films to varying degrees, but in most cases the resulting changes in attendance are not as great in magnitude as with this example.

Figure 7 shows the average shares of attendance by each movie rank (again according to screen-count) for what is observed and for what could be from the *proportional change* policy. According to this graph, there is not much distinction between the policy and the original shares of attendance as reflected by this averaging. From this graph, one can see that there might only be a little change in the overall market shares.

FIGURE 7
Predicted Change in Shares for the *Proportional Policy*



If the other policies were to be added to this graph, they too would follow so closely with the original shares that they would not be readily distinguishable. As such, this *proportional change* policy is again shown for simplicity, though it too shows little change in the average yearly market shares. These results are somewhat disappointing for this study’s purpose, but the resistance of the shares of attendances towards more being more equal seems to, again, point to the winner-take-all nature of entertainment economics and motion pictures.

Assuming a ticket price of ₩7,000 per person (or about $7), the overall change in attendance is multiplied to estimate the monetary loss for the new screen allocations. The market losses range from about –$9 million to –$38 million for whole year, assuming a conversion rate of ₩1,120 per $1 and rounding to the nearest million. Table 4 shows the costs of each program and the average weekly percentage change in HHI from the old scheme to the new one. An efficiency rating has also been computed and shown here, which is simply the cost of the program divided by the percentage point change in HHI. This cost can be thought of as the subsidy required by the government to pay to the movie industry to promote this allocation of screens and provide an incentive for the firms to behave off of profit-maximization.

TABLE 4 **Predicted Policy Results**

	Cost (Subsidy)	**Average % Change in HHI**	**Efficiency (Cost/Change)**	**Cost/ Attendee**
Change of 75	₩ 41.4 billion ($37,000,000)	*-19.91%*	₩2.0 billion ($ 1,860,000)	₩ 227 (20¢)
Change of 20	₩ 10.3 billion ($9,000,000)	*-6.58%*	₩1.5 billion ($ 1,400,000)	₩ 55 (5¢)
Linear Change	₩ 20.1 billion ($18,000,000)	*-11.72%*	₩1.7 billion ($ 1,540,000)	₩ 109 (10¢)
Discontinuous Change	₩ 21.8 billion ($19,000,000)	*-10.27%*	₩2.1 billion ($ 1,900,000)	₩ 118 (11¢)
Proportional Change	₩ 37.7 billion ($34,000,000)	*-10.89%*	₩3.4 billion ($3,090,000)	₩ 206 (18¢)
Biased Change	₩ 42.2 billion ($38,000,000)	*-12.17%*	₩3.4 billion ($3,100,000)	₩ 232 (21¢)

Currency amounts are rounded numbers and are approximate.

As can be seen, the best one would be the simple change-of-20 policy. It is the least costly and has the best efficiency rating, but it also has the least impact in lowering the weekly average HHI for screen concentration. This –6.58% change in HHI is not as big as achieved in the other screen allocation policies; so should a change of at least -10.00% be desired, the second best option seems to be the linear-change policy, as it is the second least costly and second most efficient. And, its percentage change in the HHI almost doubles that of the change-of-20 policy. The final statistic in the table shows the cost of the subsidy per movie attendee. If the government would tax movie tickets for less than a dollar, then they could perhaps be reimbursed for enforcing and subsidizing these policies.

CONCLUDING DISCUSSION

What has been done here is a demand model was formulized to predict the share of movies in South Korea's box office based primarily on its number of screens. However, since screen-count is correlated not only with market share but also the unobserved quality of the movie, instrumental variables had to be utilized to work around the resulting bias in the estimated coefficients. Once that is accounted for, this model can be particularly useful in analyzing screen-allocating policies. In the case of this study, hypothetical screen policies were formulated and plugged into the model to see how the results would turn out in order to find the most efficient system for increasing diversity in movie exhibition. However, one could even use this to look at the present screen-quota system in South Korea or other countries. One could check what the industry would look like if the screen quota system were actually binding. It would be interesting to see the results of an even more Korean-dominating industry and see how much the audience attendance would be different. Of course, one would need to make several assumptions about how to redistribute the screens towards the Korean movies, and maybe one would also have to assume the entry of additional, hypothetical movies, assuming that the supply side would also react and produce more. In the event that one wants to artificially inject imaginary films into the data to study such questions, one could draw the movie characteristics and unobserved residuals from the random distributions that are implied by the actual data. As for the innate quality of the movies, that value can be estimated from using the second regression, the one of the regression movie characteristics on the movie fixed effect coefficients, as briefly referred to in this study. In this way, one can use this model to make other kinds of counterfactual analysis.

Besides using this model for other applications, there can be a couple of other paths to proceed from this study. Generally, one way that this research could be tinkered with is in trying a nested logit model instead of the basic logit model. One might also want to change the descriptive variables of this study. For instance, one could try the number of screenings instead of screens as the key variable. Perhaps, there could be a better way to define the "star power" or "audience-attractive power" of the actor, director, and production company rather than using the two kinds of variables in this study. For example, in other studies, a movie's budget, being related to both the movie's quality and marketing power, seems to be a good predictor of box-office earnings (Prag and Casavant, 1994). However, since this kind of information is really hard to find for Korean movies, it could not be used in this study. Another way to progress from estimating a demand model would be to change the focus of this demand model to analyze another issue in the film industry. One might be interested in using this model to further decompose the innate quality of a movie. It would be interesting to see if one could correlate movie reviews with the estimated coefficient from the movie fixed effect. From these few examples, one might find a couple of ways to progress with this research to study entertainment economics.

At any rate, this area of study seems like it could only get more important as the South Korean industry develops and matures and as the Korean population becomes more accustomed to attending theaters and watching movies. With the slow increase in the average number of attendance per year, the habit of going out to the movies without checking the available selection is bound to increase. But, if this kind of spontaneous consumerism is met only with limited options at the theater, then it could possibly hinder the industry's future growth as a viable outlet for media consumption. Hopefully, this study has demonstrated a beneficial way to reasonably model movie demand and to use that model to support some kind of claim about the industry.

LIST OF MOVIES IN DATABASE

A Weekend with Marilyn Monroe
Act of Valor
Almost Che
Alvin Super Band 3
Amazing Spiderman
American Pie
Architecture 101
Argo
Avengers
Baby Turtle Toto
Bad Hero
Baksu Gundal
Band-aid
Battleship
Beauty and the Beast
Bel Ami
Big Miracle
Bijeonghan City
Billionaire
Billy and Brave Guys
Bolts and Blip
Bourne Legacy
Brave
Breaking Dawn 1
Breaking Dawn 2
Cabin in the Woods
Changing Sides
Chohanji Cheonhadaejeon
Chronicles
Cloud Atlas
Code Name Geronimo
Cold Light of Day
Company Man
Conan Warrior
Concubine
Contraband
Conviction
Dancing Queen
Dangerous Liaisons
Dark Knight Rises
Dark Shadows
Daughter from Heaven
Deranged
Dinosaurs in Korea
Don't Click
Don't Cry Mommy
Doomsday Book
Doraemon
Double
Dragon Age
End of Watch
Eungyo
Even so, One more time
Expendables 2
Extreme Thirteen
Face Blind
14 Blades
Frankenweeni
Fullmetal Alchemist
Gabi
Gan-gi-nam
Ghost Rider
Golden City Finding
Gone like the Wind
Gongmojadeul
Grave Encounters
Guardians
Happy Feet 2
Haywire
Haze
Hell's Fire
Helpless
Here Comes the Body
Howling
Hugo
Hunger Games
I AM
I am a Murderer
I am Gong-mu
I am King
I Don't Know How She Does it
Ice Age Four
Ides of March
Insidious
Iron Sky
Jackal
James Bond
Jeomjaeng-eedeul
Jesus Christ Superstar
John Carter
Jojo Banran
Journey to Forgotten World
Justice
King Abu
Koala Kid Hero
Korea
Legend of the Rabbit
Les Miserables
Letters to Momo
Life of Pi
Limitless
Lincoln Vampire Hunter
Lion King
Living Novel
Lockout
London Boulevard
Looper
The Lorax
Love Clinic
Love Fiction
Love Me Again Warmly
Machine Gun Preacher
Madagascar 3
Man Became King
Man on Ledge
Marrying the Mafia
Men in Black
Millennium Tattoo Girl
Miracle Force Power Rangers
Miss Go
Mission Impossible
Mozart Rock Opera
Mr. Cha
The Muppets Movie
My Life's Last Thing
My Little Hero
My P.S. Partner
My Way
My Wife's Everything
Naruto
Neighbors
Never-ending Story
Nico: Santa's Reindeer
Night Fall
Ninja Boy
Nutcracker
One Day
One Night Stand
One Piece
Other Policemen
Pacemaker
Papa
Paranormal Activity
Peach Tree
Perfect Game
Phantom of the Opera Anniversary
Phantom of the Opera Live
Piranha
Pokemon Hero Lesiram

Pokemon Hero Zecrom
Pokemon Kerdio
Pokemon Twinkle, Twinkle
Prince Leo
Prince Leo 2
Project 577
Prometheus
Puss in Boots
Raid
Red Lights
Resident Evil
Return of Power Rangers
Return to Base
Rock of Ages
Rum Diaries
Sadako
Safe House
Sammy Adventures 2
Savages
Scary Stories
Secret of Monster Island
Secret of the Mysterious forest Island
Sherlock Holmes
SM Town Live
Snow White
Snow White and the Hunters
Sonogong Birth
Space Dogs
Spies
Spring Snow
Step Up Four
Strange Love
Street Dance2
Suspect X
Swan Lake
Taken 2
Taste of Money
Ted
The Darkest Hour
The Divide
The Dredd
The Gray
The Hobbit
The Impossible
The Lady
The Raven
The Thing
The Tower
The Vow
Thieves
This Means War
Thor's Hammer
Thunder 11 Go
Tinker Tailor Soldier Spy
Tintin
Titanic
Total Recall
26 Years
2 Months
Typhoon Calling Spy
Ugly Duck Baby
Unbowed
Underworld Four
Untouchables
Upside Down
War Horse
War of Criminals
We Bought a Zoo
Wedding Scandal
Werewolf Boy
Woman in Black
Woman of Steel
Wonderful Radio
Wrath of the Titans
Wreck-it Ralph
Yatta-man
Yong-mun Bigab

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초 록

상영 영화 다양성 촉진:

대한민국 영화 산업의 상영관 재분배에 대한 연구

서울대학교 대학원

경제학과

콜제임스

각 상영관에 매주 다른 영화를 재할당하는 것이 관객 수에 어떤 영향을 미치는가? 본 논문은 다양한 종류의 영화가 상영될 수 있도록 장려하기 위한 상영 영화 재할당이라는 주제에 초점을 맞추어 한국 영화시장을 연구한다. 이 연구는 먼저 한국의 영화시장의 다양한 면모에 대하여 논의하고 이어서, 2012 년의 자료를 통해 확인된 영화 수요를 모델링하고 분석한다. 로짓모델과 영화 고정 효과를 사용하여, 주마다 주어진 영화를 재할당하는 상영관의 수에 주로 기반하여 영화에 대한 수요 함수를 추정한다. 또한 내생적인 도구적 변수로 상영관 수를 변수로 설정한 이유에 대해 설명한다. 추측된 수요함수는 상이한 상영관 할당 상황 하에서 가능한 스크린 배당 결과를 보여주기 위해 사용되었다. 이때 사용된 상영관 할당은 상위 20 개 영화들 중에서 더 균형적인 상영관 배분을 이끌어 낼 수 있는 방법이다. 새로운 상영관 할당을 통해 영화 상영에 다양성을 꾀할 수 있으며 이를 통해 소비자들은 더 많은 선택권과 더 큰 만족감에 대한 잠재력을 보장받을 수 있다.

주요어: movie demand, entertainment economics, logit model, discrete choice model, screen allocation, diversity

학번: 2011-24017

OTHER FIGURES

FIGURE I
Average Change in Attendance for Top-20 Films

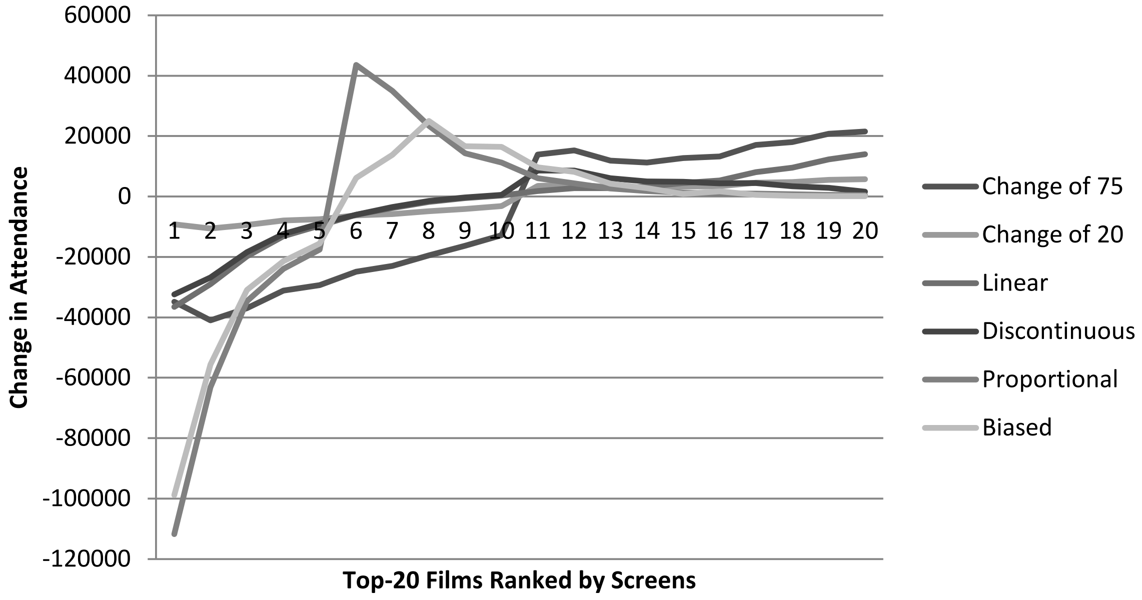

FIGURE II
Average Change in Attendance for Top-20 Films

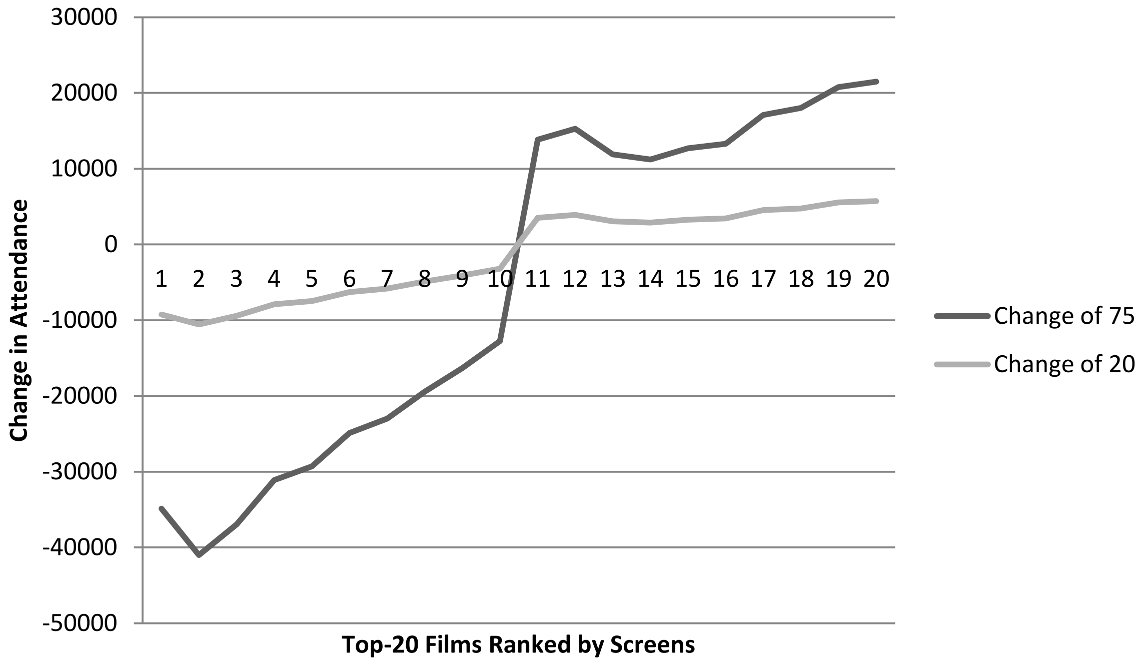

FIGURE III
Average Change in Attendance for Top-20 Films