MARKETING MODELS OF ENTERTAINMENT PRODUCTS

by

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Abstract

Television broadcasts of major events like the Super Bowl command extremely high advertising rates. It is important to evaluate the value created by this advertising tactic. The first essay develops a marketing model that illustrates a direct and an indirect effect path created by Super Bowl TV advertising in the movie industry. First, via the direct path, Super Bowl advertising directly increases initial theatrical demand for a movie. Second, through the indirect path, Super Bowl advertising first encourages more exhibitors to screen a movie, then this increased exhibition rate in turn increases initial box office revenue. Four variants of the marketing model are explored in the attempt to capture the non-linearity of the two paths and other control variables' effects. Three main results are obtained. First, Super Bowl advertising is demonstrated to affect opening box office revenues positively. Second, this positive effect occurs mainly through the indirect path, establishing the mediating role of movie exhibitors. Third, compared to other TV advertising efforts, Super Bowl advertising appears less effective if both efforts are evaluated at the same initial level. However, at current spending levels, Super Bowl advertising can still be justified.

Many entertainment service providers serve customers according to pre-announced schedules, and the timing factor can be as important as price and service quality in determining consumer demand. The second essay develops three demand models to characterize the effects of different service start times in a multiplex movie theater context. The models address two recurring issues, namely the confounding of product quality and time preference in aggregated sales data, and the difficulty of distinguishing between cannibalization and market expansion. Meaningful results are obtained by applying the models to two data sets of admission records from a multiplex movie theater in Amsterdam. First, one of the data sets is demonstrated to exhibit confounding of unobserved movie quality and moviegoers' underlying time preference, establishing the value of the demand models in disentangling these two effects in the aggregated sales data. Second, the effectiveness of the models in comparison to previous models is demonstrated in the process of discerning between cannibalization and market expansion. (Marketing Models, Movies, Entertainment Marketing)

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Chapter 1: Introduction

1. Motivation

This dissertation is comprised of two essays. Both essays address marketing problems in entertainment industries, the movie industry in particular. Entertainment products are crucial to our quality of life and vital to the economy. For example, Americans annually spend at least 130 billion hours and more than $260 billion enjoying entertainment products. More importantly, the economic significance of entertainment industries is growing rapidly: together, the industries demonstrated an annual revenue growth rate averaged at 7.5% from 1998 to 2002 (Vogel 2004).

Parallel to their growing significance for the economy, entertainment industries in general, and the movie industry in particular, are also receiving increasing attention from academics. Observing the trend that an increasing number of academic studies are conducted in relation to the movie industry, Eliashberg, Elberse and Leenders (2005) and Weinberg (2005) suggest several reasons for such growth. The main three reasons are summarized here:

1) The movie industry highlights several important dimensions of marketing problems common to both other entertainment and non-entertainment industries, such as channel relationships and timing decisions. For example, the profitability of a movie depends greatly on the timing decision. As shown by Krider and Weinberg (1998), releasing a movie head-to-head against a similar movie is usually an inferior strategy compared to releasing such competing movies at different times in the same season.
2) The rich data available in the movie industry not only provide high quality measurement of hard-to-measure marketing variables and phenomena, but also enable researchers to sort out complex causal structures, which are difficult to assess in other settings. Some researchers, such as Weinberg (2005), even refer to the movie industry as a "natural experimental

laboratory" with which to study complex relationships, which can potentially be generalized beyond the entertainment industries.

3) As one of the key industries in the entertainment business sector, the movie industry is crucial to the U.S. and global economies. For example, in the theatrical market alone, the U.S. movie industry generated $11 billion internationally in 2004. Therefore, the substantive findings of any movie research have high managerial relevance.

While the two essays in this dissertation seek to shed light on marketing practices beyond the movie industry, their empirical studies are based in the movie industry. In the following, we first describe the specific marketing problem addressed by each essay and then discuss why the movie industry is an excellent setting for the corresponding empirical study in light of the three reasons highlighted above.

1.1 Essay 1: Is There a Payoff for Playoffs?

The launch of new products is a frequently encountered marketing problem in many entertainment industries. For example, according to the Funworld data from NDP, more than 200 new video game titles were released in the three-month window from October to December, 2003. However, movie marketers are among the most sophisticated in terms of the management of new product launches. One of the launch tactics used by movie marketers is airing television commercials during major TV events like the Super Bowl and the Oscars. However, such a tactic is not cheap: a 30-second time slot during Super Bowl 2005 cost $2.4 million, almost twenty times the cost of airing the same advertisement on prime-time network TV. This is a dramatic marketing choice, but does it pay off? The objective of the first essay, "Is There a Payoff for Playoffs? Effects of Major TV Event Advertising" is to answer this question.

Why study the effects of major TV event advertising in relation to the movie industry? First, new product launches are common to a variety of product categories in both entertainment and non-entertainment industries. This issue is particularly important to the movie industry, because each movie title has a very short product life cycle and the overall profitability depends greatly on the box office performance during the release week. For 402 movies released widely in the U.S. theatrical market from 2000 to 2002, each movie on average received 45% of its total box office revenue in the opening week alone. Afterward, the percentages decreased very rapidly: 25% in the second week, 13% in the third, 7% in the fourth, and 4% in the fifth week. In fact, not all movies lasted for five weeks. Therefore, the importance of evaluating new product launch tactics such as those related to major TV advertising is highlighted in the movie industry. Second, unlike their counterparts in other industries, movie marketers air their movie commercials during major TV events before the movies are released. The causal order between the major TV event advertising and the outcomes, for example box office revenues, is therefore more apparent in the movie industry. Third, the movie industry is an inherently critical industry due to its size. In addition to providing substantive findings, the marketing models developed in this essay can be used directly by managers within the industry.

1.2 Essay 2: Good Movie or Nothing Better to Do?

Many entertainment products are delivered according to a pre-announced schedule. For example, music concerts advertise their schedule in advance in magazines and newspapers. Because consumers decide whether they wish to purchase certain entertainment products on the basis of these pre-announced schedules, the time schedule factor is as important as advertising and product quality in determining consumer demand. It is therefore important to capture consumer time preferences in the demand models for entertainment service providers. However, there are two difficulties in building the type of demand models studied here. First, underlying consumer time preferences must be disentangled from unobserved product quality in aggregate demand data. Second, the cannibalization and market expansion effects must be distinguished when new choice alternatives are added to a schedule. The objective of the second essay, "Good Movie or Nothing Better to Do? Time of Day Demand Models for Multiplex Movie Theaters", is to develop demand models that can address these two issues.

Again, there are several reasons this problem warrants study in the context of the movie industry. First, pre-announcing a service time schedule is a common practice among some service providers such as transportation companies. However, since movies are experience goods, the relative attractiveness of individual movies is typically unobservable to researchers, and such unobservability makes it more important to disentangle underlying consumer time preferences from unobserved product quality in aggregate demand data. Second, multiplex movie theaters typically do not charge differential prices for different movie titles. This eliminates any possible confounding of quality and price effects from the sales data. Our demand models therefore demonstrate the two major issues more clearly. Third, the movie exhibition industry generated tens of billions of dollars in 2004. The substantive findings generated and marketing models developed in this essay are of clear benefit to this important industry.

2. Overview

2.1 Essay 1: Is There a Payoff for Playoffs?

This essay argues that there are two potential effects of major TV event advertising, namely a direct effect on consumer demand and an indirect effect on consumer demand mediated through the attraction of more downstream channel members or retailers. Focusing on the U.S.

movie industry from 2000 to 2002, we empirically test these two potential causal paths in the case of TV advertising during the Super Bowl, which is the largest major TV event each year. We demonstrate that Super Bowl TV advertising by a movie affects opening week box office revenue mainly by indirectly attracting more movie exhibitors and thereby increasing product availability, which in turn increases initial box office revenues. More importantly, we also compare the effects of Super Bowl TV advertising to those of other TV advertising expenditures on potential exhibitors and ultimately initial box office demand. Our results demonstrate that Super Bowl TV advertising is not as effective as other TV advertising efforts, if both are evaluated at the same initial levels. However, using a counterfactual simulation, we highlight the fact that the Super Bowl could still be an attractive advertising opportunity when a movie also commits to substantial spending on other advertising efforts.

2.2 Essay 2: Good Movie or Nothing Better to Do?

Focusing on multiplex movie theaters, this essay develops three models to address two critical issues related to multiplex movie theaters and similar service providers, namely the confounding of product quality and time preference in the aggregated sales data, and the difficulty of distinguishing between cannibalization and market expansion. First, we extend Einav's (2003) yearly seasonality model to build a base model. Second, we further extend the base model in accordance with two approaches in the literature, the nested logit model and Ackerberg and Rysman's [AR] (2002) congestion model, which can better distinguish between cannibalization and market expansion effects when there is choice set variation. In applying the three models to two data sets from a multiplex movie theater in Amsterdam, we obtain two main results. First, one of the two data sets does exhibit the confounding of unobserved movie quality and moviegoers' underlying time preference, demonstrating the value of our demand models in disentangling these two effects in the aggregated sales data. Second, the nested logit and AR's models both indicate that the two data sets exhibit slightly more cannibalization than the magnitude suggested by the standard logit when new movie choices are added to a particular one-hour viewing time slot.

3. Organization of Dissertation

The rest of the dissertation is organized as follows. The first essay is presented in two chapters. The marketing models used to test the effects of major TV event advertising are developed in Chapter 2, and the data and the model estimation results are discussed in Chapter 3. For ease of reference, the first essay's figures, tables, appendices and bibliographies are all placed at the end of Chapter 3. We present the second essay in Chapter 4. Finally, in Chapter 5, we conclude the dissertation with a summary of the contributions, managerial implications and future research directions of the two essays.

4. References:

Ackerberg, Daniel A. and Marc Rysman (2002), "Unobserved Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects," working paper, UCLA

Einav, Liran (2003), "Gross Seasonality and Underlying Seasonality: Evidence from the U.S. Motion Picture Industry," working paper, Stanford University

Eliashberg, Johoshua, Anita Elberse, and Mark A. A. M. Leenders (2005), "The Motion Picture Industry: Critical Issues in Practice, Current Research and New Research Directions," *Marketing Science*, forthcoming

Krider, Robert E. and Charles B. Weinberg (1998), "Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game," *Journal of Marketing Research*, 35(1), 1-15

Vogel, Harold L. (2004), *Entertainment Industry Economics*, 6th ed., Cambridge University Press

Weinberg, Charles B. (2005), "Research and the Motion Picture Industry," *Marketing Science*, forthcoming

Chapter 2: Is there a Payoff for Playoffs?

Effects of Major TV Event Advertising

Part I: Model Development

1. Introduction

Television broadcasts of major events like the Super Bowl, Olymics or Oscars are commanding record-high advertising rates: a 30-second commercial cost an estimated average of $2.4 million during Super Bowl 2005[1] and $1.6 million during the 2005 Oscars (New York Times February 10, 2005). As a recurring theme in Corporate America at present is to make marketing more accountable (Businessweek December 13, 2004), it is important for both academics and practitioners to know if such a 30-second spot in a sports playoff game or an award show is worth the high cost. Consider the National Football League's Super Bowl in particular. As a 30-second prime time network TV commercial in February 2004 cost around $120,500 and had a cost per million audience of $19.85, the 2-million-dollar price tag of an advertisement during that year's Super Bowl, which had a cost per million audience of $51.26, simply cannot be justified on the basis of a cost efficiency argument. In fact, Starcom, a Chicago-based media agency, has shown that their TV-reach optimizer could use $2.3 million, the average Super Bowl rate in 2004, to build a schedule of commercials running on the other broadcast networks to achieve 60% more reach than the 30-second commercial during the Super Bowl period (Broadcasting & Cable January 31, 2005). All these facts lead to one important question: What additional value would a 30-second spot during a major TV event create compared to a mere prime time TV spot?

[1] ABC is reported to be asking for an estimated $2.6 million for each 30-second commercial during Super Bowl 2006 (New York Times April 20, 2005)

This essay argues that there are two potential effects specific to advertisements during major TV events, namely a direct effect on consumer demand and an indirect effect on consumer demand through the attraction of more downstream channel members or retailers. Focusing on the U.S. movie industry from 2000 to 2002, we empirically test these two potential causal paths in the case of TV advertising during the Super Bowl, which is the largest major TV event each year and therefore serves as an excellent illustration of the issue. In particular, we show that Super Bowl TV advertising for a movie affects the opening week box office revenues mainly by indirectly attracting more movie exhibitors so as to increase the product availability, which in turn increases the initial box office revenues. Moreover, we also compare the effects of Super Bowl TV advertising to those of other TV advertising expenditures on exhibitors and ultimately the initial box office demand. Our results indicate that Super Bowl TV advertising is not as effective as other TV advertising efforts, if we consider marginal returns at the same initial level. However, the Super Bowl is still an attractive advertising opportunity when movie advertisers also commit to substantial spending on other advertising efforts, which start generating responses in a saturation manner.

A broader purpose of the present essay is to highlight the role of downstream channel members in mediating the effects of marketing tactics such as major TV event advertising. As mentioned earlier, marketing practitioners are now under enormous pressure to be more responsible for their marketing spending. Specifically, before (and after) allocating resources in a marketing action, marketing practitioners have to know what effects the marketing action will create (and will have created). Tracking such causal effects and measuring the outcomes is now one of the top priorities among marketing practitioners. Unfortunately, as illustrated in a recent survey of the members of the Association of National Advertisers (Nail 2005), marketing practitioners are still having difficulty agreeing on the right metrics to measure marketing performance in general. As shown in Figure-1, 69% of the marketing executives surveyed think "agreeing on the right definition of marketing metrics" is one of the difficulties in their marketing accountability efforts, making it the second most cited difficulty. More alarming is the fact that among the metrics marketing practitioners are currently using and/or will adopt (as shown in Figure-2), there is none explicitly tracking the effects of marketing initiatives on retailers in particular or downstream channel members in general.

Such a lack of attention to the metrics of the distribution channel is somewhat mirrored in academic research on marketing accountability. Rust et al. (2004) propose a chain of marketing productivity framework to help academic researchers put various research literatures and potential research directions into a marketing accountability perspective. Their framework is shown in Figure-3. While the framework covers many aspects of the chain from marketing expenditures to shareholder values, one crucial element is apparently absent. That is the mediating role of downstream channel members. We argue that in addition to customer impact, tactical actions would also create impacts on the downstream channel members, which in turn affects consumer demand. Major TV event advertising like Super Bowl advertising provides an abundance of anecdotal examples to illustrate this mechanism. When Master Lock ran its first commercial during the Super Bowl in 1974, the primary target was not consumers but distributors (Kanner 2004, p.127-128). In the subsequent twenty years, when Master Lock committed a large portion of its yearly marketing budget to Super Bowl advertising, the company reminded the hardware wholesalers that their premium pricing was well justified by the strong brand equity. In other words, distributor response is a potentially crucial factor mediating the effect of Master Lock's Super Bowl advertising effort. If one attempts to use the extant consumer-based marketing metrics to measure the effect of Master Lock's Super Bowl advertising, an incomplete understanding would result.

In a nutshell, the present essay intends to make two levels of contribution. First, we study the worth of major TV event advertising by focusing on the U.S. movie industry's use of Super Bowl TV advertising to launch new movies. Second, we highlight the mediating role of downstream channel members in a broader perspective of marketing accountability.

This essay consists of two chapters, namely "Model Development" and "Data Analysis." The next section of this chapter more specifically discusses how this essay advances the marketing literature. We then discuss in section 3 the rationale for using the movie industry for our empirical investigation. Section 4 introduces our models. The next chapter continues with section 5 and section 6, which describe the data variables and discuss the estimation results. Section 7 presents further analysis on the basis of the estimation results. The limitations of this research, and further research directions, are discussed in section 8.

2. Related Literature

As stated in the previous section, this essay intends to contribute at two levels, examining the effects of the tactic of major TV event advertising, and demonstrating the mediating role of downstream channel members in the broader perspective of the marketing productivity chain. We first review the literature from the broader perspective and then use a previous major TV event advertising study to motivate our main research questions.

2.1 Marketing Accountability

In their widely cited papers in the marketing metrics literature, Srivastava, Shervani and Fahey (1998, 1999) introduce a conceptual framework outlining the chain from tactical marketing activities to ultimate shareholder value. Figure-4 reproduces their marketing-shareholder value framework. The main tenet in their framework is that in managing market-based assets, marketers should aim at four shareholder value drivers, namely accelerating cash flows, enhancing cash flows, reducing risk (vulnerability and volatility of cash flows), and enhancing the residual value of cash flows. An important insight from the framework is the importance of measuring market-based assets. Marketers must have some measures of market-based assets before being able to manage them. While Srivastava et al. discuss two types of relational market-based assets - customer relationship and partner relationship - subsequent market metrics studies primarily focus on customer relationships. In particular, a growing amount of research effort is devoted to measuring the lifetime values of customers (e.g., Werner and Kumar 2000; Niraj, Gupta and Narasimhan 2001) and modeling how customer behaviors would be influenced by different tactical marketing activities (e.g., Rust, Lemon and Zeithaml 2004). In contrast, partner relationship in general and channel relationship in particular are other important relational market-based assets in Srivastava et al's framework, but are apparently absent in the extant marketing metrics literature. An intended contribution of this essay is to highlight the importance of distribution channel in this literature stream.

A major challenge related to measuring distribution channels is that downstream channel members are independent decision makers, just like consumers, but their behaviors only facilitate (as opposed to directly generate) cash flows from consumer purchases. From a marketing productivity chain perspective, we have to understand a two-part causal path, namely how a tactical marketing action would influence the downstream channel members' behaviors and how the resultant downstream channel members' behaviors would influence consumer purchases.

Relatively little academic attention has focused on examining the first part of the path or investigating both parts simultaneously. However, the second part is relatively well established in the marketing literature. Specifically, as reviewed by Reibstein and Farris (1995), there is a robust finding in the literature that the cross-sectional relationships between brand share and retail distribution in the packaged goods industry show a convex pattern. In other words, brands with greater distribution coverage tend to achieve higher sales revenues per point of distribution. Figure-5 illustrates this typical pattern. As argued by Farris, Olver and De Kluyer (1989), the convex line is due to the fact that retailers do not stock all the competing brands. Some consumers therefore cannot find their preferred brands at retail outlets within their sphere of convenient access, and are forced to switch to the brands carried by most retailers.[2]

While not explicitly studying the shape of the sales responses with respect to distribution, previous research work has shown the presence of a relation between sales and distribution in the movie industry. For example, Jones and Ritz (1991) show that a diffusion model incorporating retailer actions without the contagion effect among consumers can still fit the weekly box office revenues of a sample of movies as well as the more sophisticated Bass models do. Despite the fact that the small degree of freedom in their model estimation may limit the generalizability of their results, Jones and Ritz's study successfully sheds light on the potential role of distribution channels in movie launches and attracts more academic attention in this area. Sawhney and Eliashberg (1996), for example, explicitly model the effect of product availability in a diffusion model for new movies. They divide a consumer's movie viewing behavior into a time to decide and a time to act. Even if a consumer decides to see a movie after being influenced by word-of-mouth or other communication campaigns, unless the movie is available, the consumer may still not see the movie (at least not in a theater). When modeling the international diffusion of U.S. movies, Neelamegham and Chintagunta (1999) found that the number of screens is a significant predictor of box office sales in various countries. It is clear that, similar to packaged goods industries, product availability is also a significant factor in the consumer purchase of movies.

[2] In the hypothetical case where all retailers carry all competing brands of a category and all consumers' tastes are similar across different geographical locations, all consumers should be able to find their preferred brands at every retailer and the sales should be simply proportional to the distribution coverage. The dotted straight line in Figure-5 represents this hypothetical case.

On the other hand, to the best of our knowledge there are no studies examining the effect of tactical marketing activities on distribution channels.[3] In particular, although studies like Parson (1974) and Elberse and Eliashberg (2003) shed light on how advertising expenditures in general influence distribution intensity, it is still not clear whether the advertising expenditures should be allocated to a specific marketing tactic like major TV event advertising or not. As shown by Mantrala, Sinha and Zoltners (1992), the allocation of marketing resources to various marketing tactics is as important as determining the total resource level. Therefore, it is non-trivial to understand the effects of specific advertising tactics. This essay extends Parson (1974) and Elberse and Eliashberg (2003) by focusing on a specific tactical action, namely major TV event advertising. First, we focus on the advertising expenditure in the pre-launch period. This variable is more specific than the total advertising expenditures used by Elberse and Eliashberg, which cover advertising efforts in both pre-launch and post-launch periods, and different from the post-launch advertising expenditures used by Parson. Furthermore, we separate the pre-launch advertising expenditure into the allocation to Super Bowl advertising and other TV advertising efforts. By allowing these two tactics to have differential effects on the downstream channel members and in turn consumer demand, we go beyond considerations of what level of advertising expenditure a new product should invest to how the advertising expenditure should be allocated.

[3] However, there are theoretical studies arguing that launch advertising in general can attract more distribution points. For example, some game theorists have formalized launch advertising expenditure as a product quality signaling game between upstream channel members and their downstream partners (e.g., Chu 1992, Desai 2000). The separating equilibrium is usually that the manufacturers of the low demand products finding it too costly to imitate those of the high demand products to spend a large sum of launch advertising.

2.2 Major TV Event Advertising

Being an important marketing tactic, it is surprising that major TV event advertising has not received much academic attention. Studies like Newell and Henderson (1998); Newell, Henderson and Wu (2001); or Tomkovick, Yelkur and Christians (2001) only use the Super Bowl as a field setting to examine the effects of various design and media factors. Their studies explain only variations in commercials placed in the Super Bowl, but not the more interesting variations, such as the differences between commercials placed in the Super Bowl and those not in it. A notable exception is an exploratory study by Yelkur, Tomkovick, and Traczyck [YTT] (2004). They found that movies that advertised during the Super Bowl achieved around 40% greater box office revenues than a matched sample of mass-market movies. However, this finding is weakened by their methodology and several potential confounding variables, for which they did not control. First, the main method used by YTT was to compare the mean box office revenues of two groups, Super Bowl-advertised movies and non-Super Bowl-advertised movies. When they attempted to control for the factors of release date and production budget, they simply cut out movies released between September and January and/or movies with production budgets lower than US$35M. We argue here that this may not be the most desirable method of controlling for these two factors, and suggest an alternative method. Specifically, YTT's way of dropping movies released between September and January is potentially equivalent to dropping movies with a gross as big as the Super Bowl movies. In fact, as suggested by Krider and Weinberg (1998), movies with similar appeal would avoid head-on competition by releasing in a different time of year. By dropping movies released in periods different from those of the Super Bowl-advertised movies, YTT are essentially excluding movies that are more similar to Super Bowl-advertised movies from their matched sample (non-Super Bowl-advertised movies), and keeping the more dissimilar ones, artificially making the two groups more dissimilar. In other words, YTT's attempt to control for one confounding factor is potentially creating another confounding problem. To improve on this method, the present study will control for the differences in release dates by explicitly capturing the potential effect of movies released in different Hollywood seasons. Instead of dropping some observations, we include all observations but statistically control for their different release dates by including some Hollywood seasons variables in our econometric models. On the other hand, another exclusion in YTT's sample is movies with production budgets lower than $35M. While this exclusion may not make the matched samples more dissimilar, as above, the rich information provided by the continuous variable of production budget is somewhat lost by making the production budget a binary variable. Instead, this study will keep production budget as a continuous variable and statistically control for its potential confounding with Super Bowl TV advertising tactic by explicitly capturing its effect in our models.

Moreover, there are two factors for which YTT have not controlled in their study, but which are potentially confounding with the factor of Super Bowl TV advertising. First, as shown in Table-6, Super Bowl-advertised movies tend to have higher total expenditure related to other TV advertising opportunities (*TVAD*) than non-Super Bowl-advertised movies in the launch period. It is possible that the higher box office performance of Super Bowl-advertised movies is due to such high total TV advertising expenditure, rather than the specific commercials during the Super Bowl. In other words, only how much a movie studio spends matters. Where it spends (Super Bowl or other prime time network TV programs) does not. It is therefore important for the current study to measure both Super Bowl and other TV advertising expenditure in the pre-launch period. In fact, by including both expenditures, we can answer a very important question: "Is Super Bowl TV advertising more effective than other launch TV advertising opportunities?" YTT only attempt to determine whether Super Bowl TV advertising generates a non-zero effect on box office revenues. However, the null effect is not a sufficient benchmark to examine the true worth of Super Bowl TV advertising. For marketing practitioners, it is more important to know if Super Bowl TV advertising can generate more impact than other alternative launch tactics. Even if commercials during the Super Bowl can generate a non-zero effect, as long as there are other alternatives which can generate more effects, marketing practitioners would not allocate any resources on Super Bowl TV advertising. In other words, the benchmark to which Super Bowl TV advertising should be compared is the effect of other tactical alternatives, rather than the null effect. Therefore, we will use other launch TV advertising as the more meaningful benchmark in the present study.

Second, as we can see from Table-6, Super Bowl-advertised movies tend to start their TV campaign much more ahead of their release dates (*LEAD*) than non-Super Bowl-advertised movies. Therefore, it is possible that the superior box office performance of Super Bowl-advertised movies is caused by the earlier TV campaign start date. In other words, it is when a movie studio starts spending, as opposed to where it spends, that makes the difference. Therefore, the time lag between a movie's launch TV campaign start date and its release date must be controlled for so as to disentangle the true effect of Super Bowl advertising from this confounding factor.

More importantly, YTT do not look at the detailed mechanism of how Super Bowl advertising works. In particular, the mediating role of downstream channel members and exhibitors in the movie context is overlooked. As argued in Section 1, the 2-million-dollar price tag of Super Bowl advertising cannot be justified on the basis of cost efficiency. What makes Super Bowl advertising worth such a high cost? Marketers and advertising agents have cited various factors ranging from corporate esteem, employee morale, trade support, and public relations, to plenty of water-cooler talk. For example, InsightExpress found through an online survey in 2004 that 50% of the 500 respondents were watching the game for the commercials and 58% said they pay closer attention to the ads during the Super Bowl than those they see every day (Advertising Age Jan 31, 2005). This suggests that Super Bowl TV advertising is reaching more "engaged" consumers, who probably devote more mental resources to processing the advertising information. Therefore, research companies generally found the week-later recall of Super Bowl advertising better than recall of other prime-time advertising (Advertising Age Jan 31, 2005).

This essay focuses on the generally overlooked trade support factor. As discussed earlier, we hypothesize that Super Bowl TV advertising has two paths to influencing opening week box office revenues. First, there is a direct path, in which Super Bowl TV advertising directly increases the demand of moviegoers. Second, there is an indirect path, which consists of two parts. First, Super Bowl TV advertising attracts more movie exhibitors to show the movies. Then, increased product availability enhances final sales revenues.

In summary, there are three research questions central to this essay. First, we re-examine the effect of Super Bowl TV advertising using a method improved from YTT. Second, by introducing the mediating role of movie exhibitors, we decompose the effect of Super Bowl TV advertising into two potential causal paths. Third, we compare the effect of Super Bowl TV advertising to a more meaningful benchmark, namely the effect of other launch TV advertising.

3. Movie Industry

Among the many U.S. industries adopting the popular tactic of Super Bowl TV advertising, why is it so interesting to focus on the movie industry? There are four factors making the movie industry a powerful setting in which to study the effects of advertising: 1) an inherently interesting question, 2) minimal advertising development cost, 3) temporal order, and 4) large sample size.

First and foremost, the role of the distribution channel in mediating the effects of Super Bowl commercials is inherently interesting. With the cost of a 30-second spot during the Super Bowl exceeding $2 million, it is unclear why more than half of the movies that are advertised during the Super Bowl are not released to the market until three or more months after the Super Bowl is played (as shown by the long time lag from Super Bowl to the release week in Table-3). It would be surprising if consumers remembered advertising that they had seen more than three months earlier. This is especially surprising given that in a typical week, the Hollywood studios release between two and four movies, with an average advertising budget in 2003 of $35 million (MPA Market Statistics 2003). In other words, more than 24 new movies are likely to be introduced into the market before the movies seen during the Super Bowl are released in movie theaters in the United States.

Second, almost all commercials for movies are made by cutting and pasting scenes from the actual films. On the other hand, developing a TV commercial in other product categories can be expensive, and more importantly, the effectiveness of the TV commercial may vary greatly from one campaign to another. For example, in addition to paying for the Super Bowl time slots to air their commercials, Budweiser each year also hires several advertising agents to develop different commercials specifically for the Super Bowl. This practice does not only confound the advertising media cost with development costs but also entails variations in different advertising campaigns' effectiveness. In contrast, a movie's TV commercials involve primarily the media costs only. This allows us to study the net effect of our focal media buying decision: Super Bowl or not. Moreover, even if there is more than one version of commercials for a movie, all versions are highly correlated with the perceived quality of the movie. In other words, the effectiveness of different versions is relatively consistent, which allows us to focus on Super Bowl advertising versus other TV advertising opportunities by summing all other TV advertising expenditures.

Third, the response of retailers in the movie industry is more causally apparent than in other industries. Exhibitors have to allocate their scarce "shelf space" to movies (particularly during the peak summer season which starts in May) and base their judgments on the expected sales of movies. Super Bowl advertising may act both as a signal to exhibitors of the expected performance of a movie and also have a direct impact on their decisions to book a movie. In fact, a major trade show in which exhibitors make commitments to showing movies, Showest, occurs every year in Las Vegas in March. Thus, the Super Bowl may be well timed to stimulate exhibitor awareness and interest in a movie. On the other hand, much of the advertising expenditure, and certainly the Super Bowl TV advertising, are spent before the movie is released. For example, in a sample of 398 mass-market movies released between 2000 and 2002, more than 95% of the movies allocated more than 70% of their total TV advertising expenditures before and during the opening week. Thus, the effect of Super Bowl advertising on opening week sales can be measured without the need to consider purchase feedback effects.

Last but not least, there are a sufficient number of movies released each year for us to conduct a statistical analysis of these effects without needing to rely on a small set of case studies. In our sample of movies released between 2000 and 2003, there were 19 that advertised during the Super Bowl.

4. Model Development

We limit the scope of the present essay to the opening week box office revenues. There are two reasons. First, as the consumers' and retailers' decisions in the second week and onwards would usually be influenced by additional factors such as the movie's ranking in the previous weeks (e.g., De Vany and Walls 1997) and "sliding scale" revenue sharing contracts between movie studios and individual theaters (e.g., Swami, Eliashberg and Weinberg 1999), which are not antecedents to the launch advertising decision, we believe the complexity of adding these factors to our study would not generate much additional insight for our main focus, namely using major TV event advertising as a new product launch marketing tactic. Second, as noted by Neelamegham and Chintagunta (1999), the mean first week viewership of their U.S. movie sample is almost double the mean weekly viewership in the U.S. and 13 other countries. This suggests that the first week box office sales are very critical to a movie's ultimate profitability. Therefore, it is non-trivial to study whether a specific launch marketing tactic is more effective than others in influencing the first week box office sales.

We formalize the research questions discussed in the literature section into three hypotheses:

H1: Replication of Super Bowl TV Advertising Effect: Super Bowl TV advertising increases the opening week box office revenues.

H2: Mediation of Movie Exhibitors: Through the mediation of movie exhibitors, Super Bowl TV advertising increases the opening week box office revenues along two paths. A) Super Bowl TV advertising first increases the number of movie exhibitors. Then, the increased number of movie exhibitors increases opening week box office revenues. B) Super Bowl TV advertising directly increases opening week box office revenues.

H3: Effectiveness of Super Bowl and other TV Advertising opportunities: Super Bowl TV advertising is as effective as other TV advertising opportunities.

4.1 Variable Conceptualization

In order to test these hypotheses, we use three groups of variables, namely endogenous variables, main exogenous variables and other exogenous variables. Table-1 lists the specific definitions of these variables. We will discuss the conceptualization of the variables here and the detailed operationalization in next chapter.

Endogenous Variables:

There are two endogenous variables in our model: opening week box office revenues (denoted as BO_j), and opening week number of theaters engaged for the movie (denoted as $THEATER_j$). These essentially represent the decision outcomes of two market participants, namely moviegoers and movie exhibitors.

Main Exogenous Variables:

According to 2003 MPAA market statistics (Table-2), TV advertising was the major medium used by movie distributors from 2000-2002. We therefore use TV advertising expenditure as a proxy for total advertising expenditure in the pre-launch period. Specifically, our two main exogenous variables are Super Bowl TV advertising expenditures ($SUPERBOWL_j$) and total expenditures on other TV advertising opportunities prior to movie release ($TVAD_j$).

In order to identify the true effect of Super Bowl TV advertising, among other factors, we have to control for the total launch TV advertising expenditure, which is one of the potential confounding factors in YTT as discussed earlier. $TVAD_j$ is therefore used to distinguish the effect of Super Bowl TV advertising from the effect of "high" advertising expenditure in the pre-launch period. In particular, if $SUPERBOWL_j$ is found to be an insignificant factor when the total launch TV advertising expenditure is controlled for, it suggests that a new product launch's sales only depend on how much advertising expenditure is behind the launch, and it does not matter where such advertising expenditures go (either Super Bowl or other network TV programs).

Note that $TVAD_j$ does not double-count $SUPERBOWL_j$. This allows us to compare the effectiveness of the two types of advertising opportunities as in H3. Furthermore, as discussed in the movie industry section, these two expenditures are made prior to the realization of the endogenous variable of box office revenue and theater numbers, therefore establishing a relatively clear causation order.

Other Exogenous Variables:

In addition to total launch TV advertising expenditures, TV campaign start date is the other potential confounding variable with Super Bowl TV advertising. We therefore include the duration between a movie's major TV campaign start date and its release date ($LEAD_j$) in our model. If the success of Super Bowl-advertised movies actually does not depend on where they advertise, but when they start advertising, $LEAD_j$ should remove the effect of Super Bowl TV advertising.

Similarly, eight more exogenous variables will be used to control for other potential confounding effects with our main exogenous variables. In particular, four exogenous variables are related to the unobserved expected quality of individual movies. The expected movie quality is important because moviegoers' decisions whether to purchase tickets for a movie in its opening week are primarily based on the expected movie quality. Similarly, theater managers decide if they will show the movie in their movie theaters based primarily on the expected number of tickets sold. In other words, expected movie quality is a main factor determining the two endogenous variables, namely BO_j and $THEATER_j$. While our two TV advertising expenditure variables are treated as exogenous here, one may argue that these advertising decisions are in fact determined endogenously by the movie studios. Specifically, when a movie studio has a movie with high expected quality, the studio is likely to increase total launch advertising expenditure to make more potential moviegoers aware of the movie. If we as researchers do not have any measures for expected movie quality in our model, we would only observe that larger launch advertising expenditures always lead to higher theater numbers and higher box office grosses, and would be misled in conclusions related to the effect of advertising expenditures, which is potentially confounded with the expected quality. Therefore, it is very important to control for expected movie quality. As movie is an experience good (Nelson 1970), moviegoers and even theater managers can only use cues to infer the expected quality. Our model includes four cues available to theater managers and moviegoers, namely production budget ($BUDGET_j$), pre-release buzz ($BUZZ_j$), publicity generated (PUB_j) and critic reviews ($CRITICS_j$). While we argue these four cues are reasonable proxy variables for expected movie quality, we acknowledge that they do not completely represent expected movie quality and it is possible that some dimensions of the expected movie quality, which are not captured by these proxy variables, have potential influences on the parameter estimates of Super Bowl advertising effect.

Moreover, to control for the possibility that Super Bowl-advertised movies tend to be a particular type of movies, and that this particular type of movie would usually do better than others in terms of box office revenues, we include two sets of variables to characterize the genre ($GENRE_j$: Action, Comedy, Drama or Family) and MPAA rating ($MPAA_j$: G, PG, PG-13 or R) of the movies.

As discussed earlier, we control for the potential confounding of Super Bowl-advertised movies and their tendency to release before the end of the summer season using a set of binary variables to indicate in which Hollywood seasons the movies open (*$SEASON_j$*: January–April, May–August, September–October, or November–December). Moreover, as moviegoers have more free time to visit movie theaters during holidays, we capture this possibility with a binary variable, *$HOLIDAY_j$*, to indicate whether the opening week covers any of the eight major U.S. holidays (New Year, Martin Luther King Day, Presidents Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, and Christmas).

Finally, different movie distributors may have differential powers in signing up movie theaters. To capture this possibility, a set of variables is used to indicate different major distributors (*$DISTRIBUTOR_j$*: Buena Vista/Miramax, Warner Brothers/New Line, Paramount, Sony, Fox, and Universal).

4.2 Conceptual Model

Corresponding to H1 and H2, the relations among the endogenous and main exogenous variables are hypothesized as in Figure-6a and Figure-6b. Figure-6a is a diagram showing the two paths of Super Bowl TV advertising effect and other launch TV advertising effect on box office revenues. The first path is a direct effect from the two TV advertising efforts. The second path is an indirect effect mediated by the movie exhibitors, as discussed previously. We can test H2 using this model. Figure-6b is an alternative model, in which the two types of TV advertising efforts only have direct effects on box office revenues and the movie exhibitors. Unlike the two-path model, the single-path model does not allow movie theaters to influence the box office revenues, essentially omitting the second part of the indirect path of the two-path model. Such an omission allows us to test a replicated model of YTT, as hypothesized in H1, with several key potentially confounding factors now being controlled for. More importantly, by comparing the two-path model with the single-path model, we can examine whether the direct effect from TV advertising on box office revenues would be reduced once the mediating role of movie exhibitors is allowed. Note that this testing approach is similar to Baron and Kenny's (1986) mediation analysis, which uses three regression models, namely 1) regressing the mediator on the independent variable, 2) regressing the dependent variable on the independent variable, and 3) regressing the dependent variable on both the independent variable and the mediator. As we discuss the estimation in more detail later, rather than estimating their regression models 1 and 2 separately, our single-path model estimates the two models as a seemingly unrelated regression (SUR) model, also allowing us to test whether our independent variable, $SUPERBOWL_{j,}$ affects the mediator, $THEATER_{j,}$ and the dependent variable, $BO_{j,}$ separately. On the other hand, our two-path model is in fact a more sophisticated version of Baron and Kenny's third regression model.

Note that Figure-6a and Figure-6b also characterize the temporal order of the movie theater managers' and moviegoers' decisions. In particular, movie exhibitors may begin to consider whether or not to screen a specific movie as early as during exhibitor trade shows like Showest, but they have to finalize their screening decision on the Monday preceding the release date (Swami, Eliashberg and Weinberg 1999). On the other hand, potential moviegoers may make up their mind about going to watch a specific movie very early on, but they do not need to make any commitment until the moment they show up in front of the box offices. In brief, the variable *THEATER* is determined a week before the realization of *BO* in the opening week.

The temporal order of our two endogenous variables leads to two implications. First, variables like $TVAD_j$, $BUZZ_j$ and PUB_j need to be defined differently for *BO* and for *THEATER*. Specifically, TV advertising efforts in the release week are not observed nor considered by movie exhibitors when making their screening decisions. In contrast, potential moviegoers can observe, and would be influenced by, the release week's TV advertising efforts. Denote

$TVAD_{-1,j}$ as the total TV advertising expenditure prior to the release week and $TVAD_{0,j}$ as the total TV advertising expenditure prior to and including the release week. $TVAD_{-1,j}$ influences movie exhibitors' screening decisions ($THEATER_j$), while $TVAD_{0,j}$ influences release week box office sales (BO_j). Similarly, we denote $BUZZ_{-1,j}$, $BUZZ_{0,j}$, $PUB_{-1,j}$ and $PUB_{0,j}$ as the buzz in the week prior to the release week, the buzz in the release week, the total amount of publicity up to but not including the release week, and the total amount of publicity up to and including the release week. While $BUZZ_{-1,j}$ and $PUB_{-1,j}$ influence $THEATER_j$, $BUZZ_{0,j}$ and $PUB_{0,j}$ influence BO_j. Also note that the cumulative TV advertising expenditures ($TVAD_{-1,j}$ and $TVAD_{0,j}$) and the total amount of publicity ($PUB_{-1,j}$ and $PUB_{0,j}$) are stock variables, while $BUZZ_{-1,j}$ and $BUZZ_{0,j}$ are flow variables. By definition, the relations between $TVAD_{-1,j}$ and $TVAD_{0,j}$ and between $PUB_{-1,j}$ and $PUB_{0,j}$ are:

$$TVAD_{0,j} = TVAD_{-1,j} + \text{TV advertising expenditure in the release week} \tag{1a}$$

$$PUB_{0,j} = PUB_{-1,j} + \text{Publicity received in the release week} \tag{1b}$$

On the other hand, the relationship between $BUZZ_{-1,j}$ and $BUZZ_{0,j}$ is less clear. Future research efforts may explicitly model this relation.

Another implication from the temporal order of *BO* and *THEATER* is that the other exogenous variable, $CRITICS_j$, is only relevant to *BO*. In particular, as critic reviews are only available in the release week, $CRITICS_j$ can affect only *BO*. However, one should note that some variables are specified to influence either $THEATER_j$ or *BO,* not because of the temporal order but due to other reasons. First, $SEASON_j$ and $HOLIDAY_j$ influence *BO* only, not because of the temporal order, but rather due to the fact that most theater managers do not increase or decrease the total number of movie theaters according to different times of year. Similarly, the specification that $DISTRIBUTOR_j$ would influence only $THEATER_j$ is due to the previous discussion that $DISTRIBUTOR_j$ variables are used to capture the differential "pushing" abilities of different distributors on movie exhibitors.

4.3 Estimation Models

We are now ready to discuss the econometric model corresponding to the two-path and single-path models (Figure-6a and Figure-6b). First, we use a system of two simultaneous equations to capture the relations in the two-path model:

$$THEATER_j = f_1(SUPERBOWL_j, TVAD_{-1,j}, BUDGET_j, LEAD_j, BUZZ_{-1,j}, PUB_{-1,j}, GENRE_j, MPAA_j, DISTRIBUTOR_j, \varepsilon_1) \quad (2)$$

$$BO_j = f_2(THEATER_j, SUPERBOWL_j, TVAD_{0,j}, BUDGET_j, LEAD_j, BUZZ_{0,j}, PUB_{0,j}, GENRE_j, MPAA_j, SEASON_j, HOLIDAY_j, CRITICS_j, \varepsilon_2) \quad (3)$$

Here, $f_1(.)$ and $f_2(.)$ are the functions and ε_1 and ε_2 are the error terms for *THEATER* and *BO* respectively. As the two-path and single-path models are nested, the system corresponding to the single-path model can be obtained by omitting $THEATER_j$ in equation (3). For brevity, we will discuss only the two-path model in the rest of this section.

We explore four models with different functional forms, $f_1(.)$ and $f_2(.)$. There are two reasons for this approach. First, it is important for our comparison of the effectiveness of Super Bowl and other TV advertising as these functional forms determine the shapes of responses of *THEATER* and *BO* with respect to various variables and the diminishing or increasing rate of the marginal returns. Different functional forms may give different comparison results. It is very important to find the appropriate functional forms. Moreover, we can get a better sense of the robustness of our results by comparing the estimation results of different functional forms. The first two functional forms explored are the commonly used log-linear and log-log models:

M1: Log-linear

$$\begin{aligned}\ln(THEATER_j) = \beta_{1,0} &+ \beta_{1,SB} \cdot SUPERBOWL_j + \beta_{1,AD} \cdot TVAD_{-1,j} \\ &+ \beta_{1,BUDGET} \cdot BUDGET_j + \beta_{1,LEAD} \cdot LEAD_j \\ &+ \beta_{1,BUZZ} \cdot BUZZ_{-1,j} + \beta_{1,PUB} \cdot PUB_{-1,j} \\ &+ GENRE_j \cdot \beta_{1,GENRE} + MPAA_j \cdot \beta_{1,MPAA} \\ &+ DISTRIBUTOR_j \cdot \beta_{1,DISTRIBUTOR} + \varepsilon_1 \qquad \text{(2a)}\end{aligned}$$

$$\begin{aligned}\ln(BO_j) = \beta_{2,0} &+ \beta_{THR} \cdot THEATER_j + \beta_{2,SB} \cdot SUPERBOWL_j + \beta_{2,AD} \cdot TVAD_{0,j} \\ &+ \beta_{2,BUDGET} \cdot BUDGET_j + \beta_{2,LEAD} \cdot LEAD_j \\ &+ \beta_{2,BUZZ} \cdot BUZZ_{0,j} + \beta_{2,PUB} \cdot PUB_{0,j} \\ &+ GENRE_j \cdot \beta_{2,GENRE} + MPAA_j \cdot \beta_{2,MPAA} \\ &+ SEASON_j \cdot \beta_{2,SEASON} + HOLIDAY_j \cdot \beta_{2,HDY} \\ &+ \beta_{2,CRITIC} \cdot CRITICS_j + \varepsilon_2 \qquad \text{(3a)}\end{aligned}$$

M2: Log-log

$$\begin{aligned}\ln(THEATER_j) = \beta_{1,0} &+ \beta_{1,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{1,AD} \cdot ln(\delta + TVAD_{-1,j}) \\ &+ \beta_{1,BUDGET} \cdot ln(BUDGET_j) + \beta_{1,LEAD} \cdot ln(\delta + LEAD_j) \\ &+ \beta_{1,BUZZ} \cdot ln(BUZZ_{-1,j}) + \beta_{1,PUB} \cdot ln(\delta + PUB_{-1,j}) \\ &+ GENRE_j \cdot \beta_{1,GENRE} + MPAA_j \cdot \beta_{1,MPAA} \\ &+ DISTRIBUTOR_j \cdot \beta_{1,DISTRIBUTOR} + \varepsilon_1 \qquad \text{(2b)}\end{aligned}$$

$$\begin{aligned}\ln(BO_j) = \beta_{2,0} &+ \beta_{THR} \cdot ln(THEATER_j) + \beta_{2,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{2,AD} \cdot ln(\delta + TVAD_{0,j}) \\ &+ \beta_{2,BUDGET} \cdot ln(BUDGET_j) + \beta_{2,LEAD} \cdot ln(\delta + LEAD_j) \\ &+ \beta_{2,BUZZ} \cdot ln(BUZZ_{0,j}) + \beta_{2,PUB} \cdot ln(\delta + PUB_{0,j})\end{aligned}$$

$$+ GENRE_j \cdot \beta_{2,GENRE} + MPAA_j \cdot \beta_{2,MPAA}$$

$$+ SEASON_j \cdot \beta_{2,SEASON} + HOLIDAY_j \cdot \beta_{2,HDY}$$

$$+ \beta_{2,CRITIC} \cdot ln(CRITICS_j) + \varepsilon_2 \qquad (3b)$$

As the continuous variables - $SUPERBOWL_j$, $LEAD_j$, $CRITICS_j$, and PUB_j - have zero values for some observations in our data set, taking the natural log of the variables would result in undefined values. In order to allow the use of the log-log model, δ, a very small pre-set numerical value, is added to each of these continuous variables before taking the logarithm. In estimation, we set δ at 0.000001.[4] Note that, in order to ensure compatibility between the two TV advertising expenditures, δ is also added to $TVAD_j$ before the logarithm is taken.

As mentioned earlier, to compare the effectiveness of Super Bowl and other launch TV advertising (H3), the functional forms of the relations among $THEATER_j$, BO_j, $SUPERBOWL_j$, and $TVAD_j$ are very important. In particular, the log-linear model (M1) implies an increasing marginal return for the left-hand side variable as compared to the right-hand side variables in an equation. Denote Y as the left-hand side variable, which is $THEATER_j$ or BO_j; and denote X as a right-hand side variable, which is $THEATER_j$, $SUPERBOWL_j$, or $TVAD_j$. From (2a) or (3a), we can express the relation between Y and X as:

$$Y = exp(\beta_X \cdot X) \cdot k$$

where k is a constant invariant to X. As Y ($THEATER_j$ or BO_j) is always positive in our context, we assume k is positive for the subsequent discussion.

The first- and second-order derivatives are:

$$\frac{\partial Y}{\partial X} = \beta_X \cdot exp(\beta_X \cdot X) \cdot k$$

[4] Other values of δ have been tried and the estimation results are relatively robust to δ.

$$\frac{\partial^2 Y}{\partial X^2} = \beta_X^2 \cdot exp(\beta_X \cdot X) \cdot k > 0 \ \text{ if } \beta_X \neq 0$$

As we hypothesize that $\frac{\partial Y}{\partial X}$ is positive for all X in our context, β_X is expected to be positive.

Together with the positive $\frac{\partial^2 Y}{\partial X^2}$, the log-linear model assumes that Y increases with X at an increasing rate. In the case that X is $THEATER_j$, an increasing marginal return relation may make sense, as discussed in the literature section. However, in the case that X is either of the two TV advertising variables, the increasing marginal return is counterintuitive and contradictory to the results in previous advertising studies (e.g., Vakratsas, Feinberg, Bass and Kalyanaram 2004).

On the other hand, the log-log model (M2) allows the marginal return to be diminishing or increasing but in a restrictive manner. Similar to the above, we can write the relation characterized by (2b) or (3b) between each pair of our focal variables, Y and X as:

$$Y = X^{\beta_X} \cdot h$$

where h is a constant invariant to X and we assume it to be positive.

The first- and second-order derivatives are:

$$\frac{\partial Y}{\partial X} = \beta_X \cdot X^{\beta_X - 1} \cdot h$$

$$\frac{\partial^2 Y}{\partial X^2} = \beta_X \cdot (\beta_X - 1) \cdot X^{\beta_X - 2} \cdot h \qquad \begin{cases} > 0 \text{ if } \beta_X > 1 \\ < 0 \text{ if } 1 > \beta_X > 0 \end{cases}$$

Even under our hypothesis that β_X is positive, $\frac{\partial^2 Y}{\partial X^2}$ can be positive or negative, depending on whether β_X is larger than one or not. That means the log-log model allows Y to increase with X at either an increasing rate or a diminishing rate. However, this is still a very restrictive functional form. The log-log model essentially implies a constant elasticity of Y to X, restricting the percentage change of Y due to one percentage change of X to be constant over all range of X.

While we will apply both log-linear and log-log models to the data, we also explore a more flexible form for $f_1(.)$ and $f_2(.)$. First, we no longer restrict all continuous variables on the right-hand side of an equation to the same functional form. While the log-linear and log-log models are common model specifications in econometrics, their assumption that all continuous variables on the right-hand side influence the left-hand side variables in the "same" manner is arbitrarily restrictive. For example, there is no a priori reason why $THEATER_j$ and $BUZZ_j$ have to follow $SUPERBOWL_j$ and $TVAD_j$ in exhibiting constant elasticity in the log-log model, or why managerial decision variables like $BUDGET_j$ must give an increasing marginal return just like $CRITICS_j$. Therefore, while we keep the three managerial decision variables, $SUPERBOWL_j$, $TVAD_j$, and $BUDGET_j$ in the log form, we test the functional forms of other continuous exogenous variables like $BUZZ_j$ using two models, one incorporating the linear form and the other using the log form.

More importantly, since the mediating role of $THEATER_j$ is the main thesis in this essay, we use a quadratic form for $THEATER_j$ in the box office revenues equation. In other words, we regress BO_j against a linear and a squared term of $THEATER_j$. Two parameters, rather than one, are used to characterize the relation between BO_j and $THEATER_j$. We call this a log-quadratic model. By using two parameters, the log-quadratic model is more flexible than a constant elasticity model, while allowing increasing and/or diminished marginal return:

$$BO_j = exp(\beta_{THR1} \cdot THEATER_j + \beta_{THR2} \cdot THEATER_j^2) \cdot m$$

where m is a constant invariant to $THEATER_j$ and is assumed to be positive.

$$\frac{\partial BO_j}{\partial THEATER_j} = exp(\beta_{THR1} \cdot THEATER_j + \beta_{THR2} \cdot THEATER_j^2) \cdot (\beta_{THR1} + 2 \cdot \beta_{THR2} \cdot THEATER_j) \cdot m$$

$$\frac{\partial^2 BO_j}{\partial THEATER_j^2} = exp(\beta_{THR1} \cdot THEATER_j + \beta_{THR2} \cdot THEATER_j^2)$$

$$\cdot((\beta_{THR1} + 2 \cdot \beta_{THR2} \cdot THEATER_j)^2 + 2 \cdot \beta_{THEATER2}) \cdot m$$

Despite the complex form, $\frac{\partial^2 BO_j}{\partial THEATER_j^2}$ is not restricted to being either positive or negative.

For example, if $\beta_{THR1} = 0.02$ and $\beta_{THR2} = -0.000009$, $\frac{\partial^2 BO_j}{\partial THEATER_j^2}$ is negative (= –0.000014) at $THEATER_j = 1000$. If $\beta_{THR1} = 0.02$ and $\beta_{THR2} = 0.000001$, $\frac{\partial^2 BO_j}{\partial THEATER_j^2}$ is positive (= 0.000486) at $THEATER_j = 1000$.

As discussed earlier, we also allow the functional forms of other continuous exogenous variables to be different from those of the three managerial variables, *SUPERBOWL*, *TVAD* and *BUDGET*. Therefore, there are two variants of the log-quadratic model: M3 and M4. In both M3 and M4, the three managerial variables are related to $THEATER_j$ or BO_j in log-log form and *THEATER* influences BO_j in log-quadratic form. The difference lies in the functional forms of the other continuous exogenous variables, $LEAD_j$, $BUZZ_j$, $CRITICS_j$ and PUB_j. While M3 assumes that the continuous variables are in linear form, M4 assumes they are in log form.

M3: Log-Quadratic-a

$$\begin{aligned}\ln(THEATER_j) = \beta_{1,0} &+ \beta_{1,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{1,AD} \cdot ln(\delta + TVAD_{-1,j}) \\ &+ \beta_{1,BUDGET} \cdot ln(BUDGET_j) + \beta_{1,LEAD} \cdot LEAD_j \\ &+ \beta_{1,BUZZ} \cdot BUZZ_{-1,j} + \beta_{1,PUB} \cdot PUB_{-1,j} \\ &+ GENRE_j \cdot \beta_{1,GENRE} + MPAA_j \cdot \beta_{1,MPAA} \\ &+ DISTRIBUTOR_j \cdot \beta_{1,DISTRIBUTOR} + \varepsilon_1 \end{aligned} \qquad (2c)$$

$$\begin{aligned}\ln(BO_j) = \beta_{2,0} &+ \beta_{THR1} \cdot THEATER_j + \beta_{THR2} \cdot THEATER_j^2 \\ &+ \beta_{2,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{2,AD} \cdot ln(\delta + TVAD_{0,j})\end{aligned}$$

$$+ \beta_{2,BUDGET} \cdot ln(BUDGET_j) + \beta_{2,LEAD} \cdot LEAD_j$$

$$+ \beta_{2,BUZZ} \cdot BUZZ_{0,j} + \beta_{2,PUB} \cdot PUB_{0,j}$$

$$+ GENRE_j \cdot \beta_{2,GENRE} + MPAA_j \cdot \beta_{2,MPAA}$$

$$+ SEASON_j \cdot \beta_{2,SEASON} + HOLIDAY_j \cdot \beta_{2,HDY}$$

$$+ \beta_{2,CRITIC} \cdot CRITICS_j + \varepsilon_2 \tag{3c}$$

M4: Log-Quadratic-b

$$\ln(THEATER_j) = \beta_{1,0} + \beta_{1,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{1,AD} \cdot ln(\delta + TVAD_{-1,j})$$

$$+ \beta_{1,BUDGET} \cdot ln(BUDGET_j) + \beta_{1,LEAD} \cdot ln(\delta + LEAD_j)$$

$$+ \beta_{1,BUZZ} \cdot ln(BUZZ_{-1,j}) + \beta_{1,PUB} \cdot ln(\delta + PUB_{-1,j})$$

$$+ GENRE_j \cdot \beta_{1,GENRE} + MPAA_j \cdot \beta_{1,MPAA}$$

$$+ DISTRIBUTOR_j \cdot \beta_{1,DISTRIBUTOR} + \varepsilon_1 \tag{2d}$$

$$\ln(\mathrm{BO}) = \beta_{2,0} + \beta_{THR1} \cdot THEATER_j + \beta_{THR2} \cdot THEATER_j^2$$

$$+ \beta_{2,SB} \cdot ln(\delta + SUPERBOWL_j) + \beta_{2,AD} \cdot ln(\delta + TVAD_{0,j})$$

$$+ \beta_{2,BUDGET} \cdot ln(BUDGET_j) + \beta_{2,LEAD} \cdot ln(\delta + LEAD_j)$$

$$+ \beta_{2,BUZZ} \cdot ln(BUZZ_{0,j}) + \beta_{2,PUB} \cdot ln(\delta + PUB_{0,j})$$

$$+ GENRE_j \cdot \beta_{2,GENRE} + MPAA_j \cdot \beta_{2,MPAA}$$

$$+ SEASON_j \cdot \beta_{2,SEASON} + HOLIDAY_j \cdot \beta_{2,HDY}$$

$$+ \beta_{2,CRITIC} \cdot ln(CRITICS_j) + \varepsilon_2 \tag{3d}$$

Despite assuming different functional forms for the relation among our key variables of $THEATER_j$, BO_j, $SUPERBOWL_j$ and $TVAD_j$, the above four models test the three hypotheses H1-H3 in a similar fashion. First, with respect to replicating YTT's result (H1), by estimating the "single-path" versions of the four models (i.e. omitting $THEATER_j$ from the BO_j equation), we would expect $\beta_{2,SB}$, the coefficient for $SUPERBOWL_j$ on BO_j, to be positive, suggesting Super

Bowl TV advertising would have a positive effect on the box office before taking the mediating role of movie exhibitors into consideration.

Second, we test the mediating role of movie exhibitors (H2) by estimating the two-path versions of the four models, M1-M4. In addition to the direct causal path, we hypothesize that there is also an indirect casual path between Super Bowl TV advertising and box office revenues, through movie exhibitors. In particular, we expect that $\beta_{1,SB}$, the coefficient of $SUPERBOWL_j$ on $THEATER_j$, to be positive, supporting the first part of the indirect path of the Super Bowl TV advertising effect. Then, for the log-linear (M1) and log-log (M2) models, which use one parameter to capture the relation between $THEATER_j$ and BO_j, we would expect β_{THR} to be positive, supporting the second part of the indirect path. For the log-quadratic models (M3 and M4), we would expect the net effect of the two parameters, β_{THR1} and $\beta_{THR2,}$ would create a positive effect at the mean theater engagement level. Note that we also expect the inclusion of movie exhibitors as a mediator to reduce the magnitude of the direct causal path.

Finally, we compare the effectiveness of the Super Bowl and other TV advertising opportunities (H3). We could make the comparison on two bases. On the one hand, conditional on one specific functional form (M1, M2, M3 or M4), we test the constraints, $\beta_{1,SB} = \beta_{1,AD}$ and $\beta_{2,SB} = \beta_{2,AD}$. If both of the constraints are satisfied, it suggests that Super Bowl TV advertising is as effective as other TV advertising when both expenditure levels are equal (e.g., both *SUPERBOWL* and *TVAD* are zero). On the other hand, we can compare the effects of the two advertising tactics at their median expenditure levels, which are typically not equal.

4.4 Summary

A series of models has been formulated to test the comparative effects of launch TV advertising in general and Super Bowl TV advertising in particular on theater engagements and audience size in the first week of a movie's release. The next chapter discusses the data to be used, estimation methods, and results.

Chapter 3: Is there a Payoff for Playoffs?

Effects of Major TV Event Advertising

Part II: Data Analysis

5. Data Description

As our objective is to study Super Bowl-advertised movies, all of which are wide-release movies, our sample consists of wide-release movies from 2000 to 2002. In particular, similar to other empirical studies in the movie industry (e.g. Einav 2003), we use the number of theaters engaged in the opening week as our sampling criterion. There were 1445 movies released in the U.S. between 2000 and 2002. Figure-7 shows the distribution of the opening week theater numbers of these 1445 movies. As we can see, the distribution is bi-modal, with one mode at zero (67% of movies with smaller than 50 theater engagement in their opening week) and another mode at 2,500. This suggests there are two groups of movies[5]: one with the opening week theater engagement figure equal to 600 or above, and another with numbers under 600. As it is more likely for movies with high opening week theater engagement numbers to invest in launch TV advertising, we choose this group of movies as our sample[6]. Note that there is still high variability in first week engagement within this group. From 2000 to 2002, there were 402 movies with a first week engagement total equaling 600 or above. Of these 402 movies, we deleted four, which have missing values for production budget, forming a sample of 398 movies. The resultant 398 movies contribute 88% of US$25 billion, the total box office revenues for all movies released from 2000 to 2002.

[5] 600 is chosen as the cut-off point because it appears to be the inflection point of the slops of the distribution surface.

[6] Hollywood Stock Exchange also uses a similar criterion (theater engagement > 650) to define wide-release movies.

There were 19 movies advertised during the Super Bowls in our sample from 2000-2002. Table-3 lists these movies with the variables such as BO_j, $THEATER_j$, $SUPERBOWL_j$, $TVAD_j$ and $BUDGET_j$. While all the Super Bowl-advertised movies, except *Mission to Mars*, placed only one 30-second commercial during the Super Bowl events, there are non-trivial variances in other variables such as production budget and launch TV advertising spending. Also note that these Super Bowl-advertised movies were released on average 13 weeks after the Super Bowl events and, with the exception of four movies, their commercials during the Super Bowls were their first major TV advertising efforts. The time lags from Super Bowl and from the major TV advertising efforts to the release week are therefore identical.

Our exogenous and endogenous variables are constructed from several different data sources. The major sources are: 1) *Variety.com*, the website of the authoritative trade magazine in the entertainment industry; 2) *IMDb.com*, the popular interactive movie database website established in 1996 and visited by more than 25 million visitors each month; 3) *TNS/CMR*, the research company tracking TV commercials on over 425 network and cable channels in more than 75 TV markets in the United States, 4) *Entertainment Weekly*, the popular consumer magazine for entertainment, 5) *Rottomtomato.com*, a comprehensive website archiving reviews by movie critics, and 6) *Alexa*, a company tracking the web traffic created by their *Alexa* tool bar users, who have made 10 million tool bar downloads since 1997. The operationalization of our variables from these different sources is as follows:

Opening week box office revenues, BO_j: We obtained the opening week box office revenue numbers from *Variety.com*. As it is an industry practice to release new movies to theaters on Friday, an opening week's box office revenue is defined as the total box office receipts from Friday to Thursday. However, there are 52 movies in our sample that were released on a day different from Friday. For example, *Lord of the Rings: The Two Towers* started its theatrical run on December 12, 2002, which was a Thursday. The opening week box office totals for these movies are actually cumulative revenues from an "eight-day" or "nine-day" week. In order to ensure the consistent definition of opening week, we include only the box office revenues from Friday to the following Thursday for these movies. Note that we also run all models with the opening week box office revenues including the additional receipts from the earlier releases. As the results are similar to those with a seven-day week definition of BO_j, we only report the results of the seven-day week definition.

Opening week theater engaged, *THEATER*$_j$: The numbers of movie theaters engaged for individual movies in the opening week were also obtained from *Variety.com*. Note that these numbers only represent the numbers of sites showing individual movies, rather than the precise measure of the movies' availability. This is because many movie theaters in the U.S. have multiple screens and show multiple movies at the site. For example, a movie exhibitor may have two movies sharing one screen or have two screens showing the same movie. We acknowledge this as one of our data limitations.

Super Bowl TV advertising expenditures, *SUPERBOWL*$_j$: We identified the TV commercials for individual movies placed in the Super Bowls of years 2000, 2001 and 2002 from the TV recordings of the Super Bowl games from kick-off to the end of the game. While there were TV commercials for other films appearing before and after the games (e.g., during the pre-game and post-game shows), we include only the commercials appearing in the commercial breaks during the games. We then assigned the Super Bowl TV advertising expenditures to individual commercials on the basis of the average costs charged by the TV stations and the length of the TV commercials. These expenditure numbers were then verified by the data source from *TNS/CMR*.

Other TV advertising expenditures, $TVAD_{-1,j}$ and $TVAD_{0,j}$: We obtained the TV advertising expenditure data from *TNS/CMR*. Note that *TNS/CMR* defines a week from Monday to the following Sunday. As this definition differs from the Friday-Thursday definition for box office revenue, we set a "*TNS/CMR* week" to be the release week of a movie if this *TNS/CMR* week covers the Friday (and also the weekend) of the movie's release week. Therefore, the non-Super Bowl TV advertising expenditure before and including the release week, $TVAD_{0,j}$ is defined as all expenditures up to the first Sunday of the movie's theatrical run. Similarly, the non-Super Bowl TV advertising expenditure before but not including the release week, $TVAD_{-1,j,}$ is defined as all expenditures up to the last Sunday before the movie's theatrical run. Note that the next day, a Monday, is when theater managers finalize their screening decisions. $TVAD_{-1,j}$ is therefore specified to affect $THEATER_{j,}$ while $TVAD_{0,j}$ is used to explain BO_j.

Time lag from the first major TV advertising efforts to the release week, $LEAD_j$: We define the start week of a major TV campaign as the first week in which a movie's TV advertising expenditure exceeds the average cost of a network TV spot (US$61,063 in 2000-2002). The time lag between the first major TV advertising efforts and the release week is therefore defined as the number of *TNS/CMR* Monday-Sunday weeks between the campaign start week and the release week.

Production Budget, $BUDGET_j$: We obtained the estimated production budgets for 392 movies in our original 402-movie sample from *IMDb.com*. We then filled in the missing values for six more movies using information from *BoxOfficeMojo.com* and *the-numbers.com*. In the end, we are unable to find the production budgets for four movies, namely *Adam Sandler's 8 Crazy Nights*, *Simone*, *The Hot Chick*, and *The Truth about Charlie*. As there is no systematic pattern shared by these four movies and the other 398 movies, we decided to drop these four movies from our sample.

Buzz generated, $BUZZ_{-1,j}$ and $BUZZ_{0,j}$: We assume that strong interest in a specific movie, or a high level of buzz among the general public, manifests as two behaviors, namely word-of-mouth and click-of-mouse. While we do not observe word-of-mouth behavior in the present study, we are able to track online activities on a popular movie website, *IMDb.com*. Specifically, by assuming that a high level of buzz for a specific movie would lead to more related search attempts and newsgroup messages posted for the movie on *IMDb.com*, we argue that the amount of online activity related to individual movies is a reasonable proxy measure of buzz.

We constructed our click-of-mouse buzz proxy measure from a data series called *MOVIEmeter*^{TM} available from *IMDb.com*. Based on which specific movie pages its four to five million weekly visitors view, *IMDb.com* produces the weekly *MOVIEmeter*^{TM} ranking for more than 290,000 movie titles in its database. We believe online activities at *IMDb.com* are a good representation of all online activity on the world-wide web, for two reasons. First, many potential moviegoers enjoy visiting *IMDb.com* for movie information such as theatrical release dates, or to share opinions by posting and/or reading newsgroup messages for specific movies. Second, *IMDb.com* usually appears as one of the choices when people search for a specific movie using *google.com* or *yahoo.com*. *MOVIEmeter*^{TM} is therefore a good click-of-mouse buzz proxy measure. Appendix-A describes the detailed procedure used to transform the *MOVIEmeter*^{TM} ranking into our continuous variables, $BUZZ_{-1,j}$ and $BUZZ_{0,j}$.

Average ratings given by movie critics, $CRITICS_j$: Average critic ratings for individual movies were collected from *RottenTomatoes.com*. *RottonTomatoes.com* considers only accredited film critics (members of critics associations and/or those currently employed by an accredited print publication) when calculating average critic ratings. Each critic's original rating scale (e.g., star, letter grade, numeric) is first converted to a one-to-ten scale. Critic reviews without original ratings are then discarded. The average is computed on the converted rating scale.

Publicity received, $PUB_{-1,j}$ and $PUB_{0,j}$: We measure the publicity for a movie by determining the total amount of coverage the movie received in *Entertainment Weekly*, which has a circulation of 1.79 million, the largest after the number one publication, *TV Guide*, in the entertainment magazine category (Audit Bureau of Circulations). We first identified articles related to specific movies by coding the table of contents of each issue of *Entertainment Weekly*. We then classified each article into one of ten categories, e.g., Departments, News & Notes Category I, or Movie Review. We determined the amount of publicity generated by each article using the average number of pages of the category to which it belongs. Table-4 lists the ten categories and their average page number totals. For example, an article in the News & Notes Category I will be assigned a value of six, as articles in this category on average have six-page coverage. We therefore define $PUB_{0,j}$ as the sum of coverage values of all articles for movie j before and including its release week, and $PUB_{-1,j}$ as the sum up to but not including the release week. Note that each new issue of *Entertainment Weekly* is usually displayed until Friday. Therefore, we define the week of *Entertainment Weekly* from Saturday to Friday. Recall that new movies typically open on Friday. When an "*Entertainment Weekly*'s Saturday-Friday week" includes the first Saturday of a movie's theatrical run, we set this week as the release week for the movie.

Categorical variables, $GENRE_j$, $MPAA_j$, $DISTRIBUTOR_j$, $SEASON_j$ and $HOLIDAY_j$: We obtained the distributor name, MPAA rating and release date of each movie from *Variety.com* and *IMDb.com*. Starting from the twelve genre categories used by *Variety.com*, we simplify the categories into four main types, namely Action, Comedy, Drama and Family.

An Example: As the definition of a week varies slightly across different variables, especially those defined over a duration of multiple weeks, it would be useful to compare these various definitions using an example. Consider *Bridget Jones's Diary*, which was released on April 13, 2001 (Friday). Figure-8 shows how seven "duration-based variables" are defined. Opening in theaters on Friday, *Bridget Jones's Diary*'s BO_j is the box office receipt total from Friday to the next Thursday. Including the issue of *Entertainment Weekly* displayed until April 20, 2001 (Friday), $PUB_{0,j}$ for *Bridget Jones's Diary* is the sum of coverage in *Entertainment Weekly* until April 20, 2001, while $PUB_{-1,j}$ is the sum up to April 13, 2001. $TVAD_{-1,j}$ and $TVAD_{0,j}$ for *Bridget Jones's Diary* are the cumulative TV advertising expenditures up to April 8, 2001 (Friday) and April 15, 2001 (Friday) respectively (there is no need to subtract $SUPERBOWL_j$ because *Bridget Jones's Diary* did not use Super Bowl TV advertising). $BUZZ_{-1,j}$ and $BUZZ_{0,j}$ for *Bridget Jones's Diary* represent the estimated traffic to the movie's page at *IMDb.com* during the week of April 2 – April 8, 2001 and for the week of April 9 – April 15, 2001. Note that BO_j is led temporally by the main exogenous variables, $TVAD_{-1,j}$ and $TVAD_{0,j}$.

The Pearson correlation matrix of the continuous variables is shown in Table-5. Excluding the pairs of $TVAD_{-1,j}$ and $TVAD_{0,j}$, $BUZZ_{-1,j}$ and $BUZZ_{0,j}$, and $PUB_{-1,j}$ and $PUB_{0,j}$, which do not appear in the same equations, we can see there is no severe multicolinearity problem among the variables (correlation ranges from 0.029 to 0.485), except for the correlation between $BUDGET_j$ and $TVAD_j$, which is 0.690.[7] Table-6 shows the summary statistics for the continuous variables for the Super Bowl-advertised (SB) and non-Super Bowl-advertised (NSB) movies. Figure-9a and Figure-9b are the box plots of BO_j and $THEATER_j$ by SB and NSB. As expected, SB movies tend to have higher box office revenues and theater engagement in the opening week as compared to NSB, even though our sample consists of only wide-release movies. These differences may be caused by Super Bowl TV advertising or other differences between NSB and SB. Figure-9c, 9d, 9e, 9f, 9g, 9h, 9i, 9j, and 9k are the box plots for the

[7] However, as we will see in the results section, both $\mathrm{BUDGET_j}$ and $\mathrm{TVAD_j}$ give significant coefficients in most models, suggesting the estimation efficiency is not affected substantially by the multicolinearity of these two variables.

continuous exogenous variables, $TVAD_{-1,j}$, $TVAD_{0,j}$, $LEAD_j$, $BUDGET_j$, $BUZZ_{-1,j}$, $BUZZ_{0,j}$, $PUB_{-1,j}$, $PUB_{0,j}$, and $CRITICS_j$ by NSB and SB. As we can see, the distributions of SB tend to have higher means and medians than those of NSB, with the exception of $CRITICS_j$. In particular, SB movies typically have larger launch TV advertising expenditures ($TVAD_j$), higher production budgets ($BUDGET_j$), a longer lead time from the first major TV advertising effort to release week ($LEAD_j$), a higher level of pre-launch buzz ($BUZZ_j$), and more publicity (PUB_j), suggesting that they are potential confounding factors with the tactic of Super Bowl TV advertising. On the other hand, Table-7 shows the frequencies of the categorical variables by SB and NSB. While there is no apparent pattern in distributors and holidays, SB movies tend to be PG13 and R-rated Action movies released between January and August. Therefore, our models must control for the continuous and categorical variables so as to identify the true effects of Super Bowl TV advertising.

6. Model Estimation and Results

For each of our four models M1-M4, there are two versions, single-path and two-path. Each model was estimated as a system of simultaneous equations using the full information maximum likelihood method, in which ε_1 and ε_2 are assumed to be bivariate-normally distributed. We estimate the single-path models as seemingly unrelated regression (SUR) models. On the other hand, while each of the two-path models appears to be a triangular structural system and thus can be estimated as a recursive model, we still allow ε_1 and ε_2 to be correlated so as to increase the efficiency of the model estimation. Both endogeneity and simultaneity are therefore considered in the estimation of the two-path models. As we have $SEASON_j$, $HOLIDAY_j$, $CRITICS_j$, or $DISTRIBUTOR_j$ as the excluded exogenous variables to either $THEATER_j$ or BO_j, the rank order condition is fulfilled for each of the models. In other words, all parameters can be identified in the four models, M1-M4.

One binary variable of each set of categorical variables, *GENRE*, *MPAA*, *DISTRIBUTOR* and *SEASON*, is dropped for identification purposes. In particular, we drop the binary variables to indicate: 1) the movie is a family movie, 2) it is rated as G by the MPAA, 3) it is distributed by Disney, and 4) it is released in the Sept.-Oct. season. The effect of Disney's G-rated family movie is then indistinguishable from the intercept in the $THEATER_j$ equation (2a, 2b, 2c or 2d) while the effect of G-rated family movie released in the season of September and October is captured by the intercept in the BO_j equation (3a, 3b, 3c or 3d). When interpreting the effect of other binary variables, such as an R-rated movie, we should note that the estimated parameter associated with $MPAA\text{-}R_j$ captures the effects of $MPAA\text{-}R_j$ relative to the base case, a G-rated family movie released in Sept.-Oct. (by Disney if in $THEATER_j$ equation).

Since the single-path versions are nested by their two-path counterparts, we can compare each pair using a likelihood ratio statistic. The bottoms of Table-9a, 9b, 9c and 9d show such statistics. As indicated by the small p-values, the two-path version indeed has a better fit to the data than the single-path version across all models, M1-M4. We can therefore focus on comparing the two-path versions. As our models are similar to the seemingly unrelated regression (SUR) models (e.g., Green 2000, ch.5), we can assess the goodness of fit of individual models with a system-wide measure suggested by McElroy (1977). The basic notion of McElroy's measure is in line with the R^2 measure in the standard regression context. In particular, McElroy's measure evaluates the degree to which variability in the endogenous variables ($THEATER_j$ and BO_j in our case) can be explained by the model. The McElroy measures for the two-path versions of M1, M2, M3 and M4 are 0.700, 0.666, 0.706 and 0.712, respectively. In other words, M1, M3 & M4 are able to explain relatively more variability in

$THEATER_j$ and *BO_j* than the log-log model, M2. On the other hand, we can compare the four models by a model selection test. Specifically, the two-path versions of the four models are not nested with one another. We use a simple likelihood ratio-based statistic proposed by Vuong (1989) for each pair of models to test the null hypothesis that the two models are equally close to the true data generating process against the alternative hypothesis that one model is closer. Table-8 presents the statistics for each pair of models. As we can see, the two log-quadratic models significantly fit the data better than the log-linear and log-log models. Particularly, M3, the log-quadratic-a model has the best fit to the data. In the remaining portion of this section, the results of all four models will be compared. The objective is to evaluate the robustness of the findings. If a certain finding is supported by all four models, we know the findings are robust to model specification. On the other hand, in the next section, we will illustrate how marketing practitioners can use our models to evaluate marketing tactics and improve decisions by focusing on M3, the log-quadratic-a model.

6.1 Main Results

Table-9a, 9b, 9c and 9d present the parameter estimates of M1, M2, M3 and M4. The standard errors reported are robustness standard errors. In each table, we also compare our two-path model to the single-path model (which has *$THEATER_j$* omitted from the *BO_j* equation). In H1, we hypothesize that Super Bowl TV advertising will have an effect on opening week box office revenue. Across the various functional forms, the single-path versions of M1, M2, M3 and M4 all give a significantly positive estimate for $\beta_{2,SB}$, the effect of *$SUPERBOWL_j$* on *BO_j*. Note that this effect is obtained after we control for other potentially confounding variables, which are overlooked by YTT. We can therefore rule out some alternative explanations such as the idea that the higher box office revenue is due to the large launch TV advertising expenditures or an earlier TV advertising campaign, conditions which are usually associated with Super Bowl-advertised movies.

Although not posited as our main hypothesis, the effect of $SUPERBOWL_j$ on $THEATER_j$ is also found to be significantly positive in each of the four single-path model variants. In other words, Super Bowl TV advertising usually results in a higher number of movie exhibitors and higher box office revenues in the opening week. This finding naturally leads to the questions underlying our second hypothesis, H2: Does Super Bowl TV advertising attract more movie theaters, which in turn increases box office revenues? When we allow this indirect causal path, does Super Bowl TV advertising still have a direct effect on box office revenues? The two-path versions of M1-M4 hold these answers. In particular, in all four models, the effect of $SUPERBOWL_j$ on $THEATER_j$ ($\beta_{1,SB}$) is found to be significantly positive, establishing the first part of the indirect path. Then, the second part of the indirect path is also supported by the significant positive effect of $THEATER_j$ on BO_j, found in all four models. In particular, estimates of β_{THR} are statistically positive in M1 and M2. For the more flexible models, M3 and M4, the net effects of β_{THR1} and β_{THR2} are positive when $THEATER_j$ is larger than 1,041 in M3 and 754 in M4, both of which are lower than 1,892, the 25% percentile of $THEATER_j$ in our sample.[8] In brief, our model estimation results support the postulate that movie exhibitors are playing a mediating role in the causal chain from Super Bowl TV advertising to opening week box office revenues. Next, is the direct effect of $SUPERBOWL_j$ on BO_j affected once we introduce the mediator, movie exhibitors? While the two-path versions of M2 and M4 no longer show any significant direct effect ($\beta_{2,SB}$ is not statistically different from zero), the two-path versions of M1 and M3 have a smaller direct effect than their single-path counterparts. In other

[8] For M3, $\frac{\partial BO_j}{\partial THEATER_j} > 0$ when $THEATER_j > 1.041$ thousands. For M4, $\frac{\partial BO_j}{\partial THEATER_j} > 0$ when $THEATER_j > 0.754$ thousands.

words, our movie sample shows that the main effect of Super Bowl TV advertising is an indirect effect through the mediation of movie exhibitors.

In addition to demonstrating the presence of the mediating role of movie exhibitors, it is also interesting to note the form of the mediation. Except for M1: log-linear model, which restricts a priori the positive effect of $THEATER_j$ on BO_j to exhibit increasing marginal return, the log-log and log-quadratic models allow more flexibility for the relation between $THEATER_j$ and BO_j. In M2: log-log model, although β_{THR} is not statistically larger than one at the 5% level, the estimate for β_{THR} at 1.651 still suggests that there is a high chance of $THEATER_j$ exhibiting an increasing marginal return of BO_j. In the log-quadratic models, M3 and M4, the net effects of β_{THR1} and β_{THR2} exhibit increasing positive marginal returns after the critical points, 1,041 theaters in M3 and 754 theaters in M4. Both of the more flexible models suggest that movie exhibitors influence box office revenue in the opening week in a manner of increasing marginal return. In brief, all four models suggest a convex relation between $THEATER_j$ and BO_j. This pattern is consistent with the convex relation found in the packaged goods studies reviewed earlier. One may wonder why we obtain such a convex relation in the movie industry. While our current data set does not allow further study of the underlying mechanism, we speculate that when a movie can attract a major share of movie exhibitors, two additional effects may occur. First, the movies become an "event", which people enjoy discussing in social conversation. Examples are *Spider-man* and *Lord of the Rings*. Second, movie exhibitors start increasing the "availability" of the movies beyond normal movie scheduling by offering multiple screens, a factor which is beyond our unit of observation.

Similar to Super Bowl TV advertising, other TV advertising expenditures in the pre-launch period influence box office revenues mainly through the theater engagement factor. In particular, we found that $TVAD_j$ has direct positive effects on both $THEATER_j$ and BO_j in the single-path versions of M1-M4. On the other hand, once we introduce the mediation of movie exhibitors in the two-path versions of M1-M4, we find that $TVAD_j$'s effect on BO_j works only through $THEATER_j$ (significant positive $\beta_{1,AD}$ but insignificant $\beta_{2,AD}$). As discussed earlier, Elberse and Eliashberg (2003) also studied the mediating role of movie exhibitors and the advertising effect on box office sales. Although we cannot directly compare our findings to their results, because they define advertising as the total advertising expenditure over the whole theatrical run, we can still see the similarity between their findings and ours: advertising influences box office revenue mainly through the mediation of movie exhibitors.

Our third hypothesis, H3, requires us to compare the effectiveness of Super Bowl and other TV advertising expenditures. From this point forward, we discuss only the two-path models. As the indirect effects of $SUPERBOWL_j$ and $TVAD_j$ on BO_j function through the same mediator, $THEATER_j$, we focus on comparing their differential effects on this mediator as well as their direct effects on BO_j. Using the delta method, we specifically test two sub-hypotheses for each of M1-M4:

H3a: $\beta_{1,SB} = \beta_{1,AD}$ H3b: $\beta_{2,SB} = \beta_{2,AD}$

Table-10 presents the test results. As we can see, M1 tends to generate results different from the others. In M1, we can reject H3b but not H3a. However, in M2, M3 and M4, we can reject H3a but not H3b.

We focus on the group of M2, M3 and M4 first. Our failure to reject H3b is consistent with our previous finding that the direct effect of advertising is greatly reduced (to zero in most cases) once the indirect path is introduced: both $\beta_{2,SB}$ and $\beta_{2,AD}$ tend to be statistically not different from zero. On the other hand, our rejection of H3a suggests that Super Bowl TV advertising does not generate the same effect as other TV advertising opportunities. In fact, as indicated by the signs of the t-statistics, $\beta_{1,SB}$ is statistically smaller than $\beta_{1,AD}$. This implies that

Super Bowl TV advertising is not as effective as other TV advertising, if evaluated at the same initial levels.

For M1, since we fail to reject H3a, this suggests that Super Bowl and other launch TV advertising opportunities are equally effective on the indirect path. Moreover, the rejection of H3b is consistent with the above finding that there is a direct effect from Super Bowl but not other TV advertising on box office revenues.

The fact that M1 has implications opposite to those of the other models is troubling. To shed light on both sides, we need to first identify the difference between M1 and the group of M2, M3 & M4. Specifically, recall that M2-M4 all assume that the effects of TV advertising (*SUPERBOWL*$_j$ and *TVAD*$_j$) on *THEATER*$_j$ are in log-log form. As the estimates of $\beta_{I,SB}$ and $\beta_{I,AD}$ in M2-M4 are statistically smaller than one, the log-log form actually suggests a pattern of diminishing marginal return to TV advertising, which contrasts with the pattern of increasing marginal return implied by M1. In other words, the main difference between M1 and the group of M2-M4 lies in the shape of the relation between advertising and the two endogenous variables. If we restrict the relation between TV advertising and *THEATER*$_j$ and *BO*$_j$ to exhibit only increasing marginal return, as in M1, we find that Super Bowl TV advertising is as effective as other TV advertising expenditures in the pre-launch period. On the other hand, if we allow more flexibility by assuming a log-log form between TV advertising and *THEATER*$_j$, the effect of Super Bowl TV advertising is found to be not as effective as other TV advertising expenditures when both types of expenditure are evaluated at the same initial values. Upon which models should we base our conclusion? Although our model comparison criteria do not provide any conclusive support for any specific model, M1 relatively lacks face validity. Specifically, the increasing marginal return to advertising implied by M1, the log-linear model, is contradictory to previous advertising literature and intuition (e.g., Vakratsas, Feinberg, Bass and Kalyanaram

2004). We therefore argue that a log-log relation between TV advertising and $THEATER_j$ (M2-M4) is a preferred specification. In summary, based on M2-M4, we find that Super Bowl TV advertising is not as effective as other TV advertising expenditures in the pre-launch period, when both are evaluated at the same initial values.

Note that we have to qualify the statement that Super Bowl TV advertising is not as effective as other TV advertising with the condition that both expenditures are evaluated at the same initial values. This is because the diminishing marginal return could make the marginal effect of Super Bowl TV advertising higher than that of other TV advertising expenditures when the two expenditures are evaluated at two levels. Consider M3 as an example. The medians of $TVAD_{-1,j}$ and $SUPERBOWL_j$ in our sample are 8.04 and 0.00 (i.e. no Super Bowl advertising), respectively. If we evaluate a movie at these medians, the estimates of M3 would suggest that adding an extra US$1 million to $SUPERBOWL_j$ would result in a larger marginal gain than adding the same amount to $TVAD_{-1,j}$:

Scenario 1: Increase $SUPERBOWL_j$ from US$0 to US$1M

$$\frac{THEATER_{NEW}}{THEATER_{ORIGINAL}} = \frac{(\delta + 0 + 1)^{\beta 1,SB}}{(\delta + 0)^{\beta 1,SB}} = 1.09$$

Scenario 2: Increase $TVAD_{-1,j}$ from US$8.04M to US$9.04M

$$\frac{THEATER_{NEW}}{THEATER_{ORIGINAL}} = \frac{(\delta + 8.04 + 1)^{\beta 1,AD}}{(\delta + 8.04)^{\beta 1,AD}} = 1.03$$

In other words, if M3 is an adequate representation of moviegoers' and theater managers' behaviors, 50% of the movies in our sample, which have spent US$8.04M or more on $TVAD_{-1,j}$ but have not considered Super Bowl TV advertising, should recognize that Super Bowl TV advertising is indeed a very attractive advertising opportunity. We will illustrate this point further with a counterfactual simulation in the next section.

6.2 Other Results

Apart from our three main hypotheses, there are also some interesting results from the estimation of M1-M4:

1) $LEAD_j$: The duration between the major campaign start date and the release date does not have any significant effects on either theater engagement or box office revenues. As TV advertising expenditures are significant, however, it suggests that only the level of TV advertising expenditure by a movie studio in the launch period matters. On the other hand, $LEAD_j$ is only one of the dimensions characterizing a pre-launch advertising campaign for new products. For example, the detailed allocation of the pre-launch advertising budget in individual weeks may demonstrate that how (or when) the money is spent still matters. Future research is required on this area.

2) $BUDGET_j$ and $BUZZ_j$: Both production budget and pre-launch buzz influence the opening week box office only by encouraging more movie exhibitors to show the movie, if there is an effect (buzz has no effect at all in M2 and M4). Intuitively, as movie exhibitors must make their screening decisions for wide-release movies before the critics' reviews are available, they must use production budget, pre-launch advertising expenditure and buzz as "cues" to infer the movie's quality.

3) $CRITICS_j$: The significant positive effect of critics' reviews on opening week box office revenue suggests that moviegoers may infer a movie's quality in a way that differs from the movie exhibitors: once the reviews are available in the opening week, moviegoers then rely on the reviews, rather than buzz or budget, to infer movie quality and make their ticket purchase decision.

4) PUB_j: The significant positive effects of PUB_j on BO_j suggest that moviegoers are influenced by the degree of media attention surrounding individual movies. On the other hand, except for

M3, there is no significant effect of PUB_j on $THEATER_j$, suggesting theater managers are less influenced by publicity. This is an unexpected result. As PUB_j is a new measure in the movie literature, we cannot compare this to other studies using the same variable. Future movie research should attempt to replicate such a null effect on theater managers.

5) $GENRE_j$: Recall that family movies are used as the base case. The magnitude order of the three genre binaries in the $THEATER_j$ equation suggests that family and action movies tend to attract the largest number of movie exhibitors while comedies and dramas usually prompt the lowest theater engagement numbers. As the increased number of movie exhibitors in turn increases opening week box office revenue, family and action movies also tend to do better in the opening week.

6) $MPAA_j$: G-rated movies are used as the base case. Similar to genre binaries, we can use the relative magnitude of the estimates to infer that G-rated movies are the best movies to attract movie exhibitors, PG-rated movies are second, and PG13-rated and R-rated are relatively weak. Once again, as movie exhibitors play a mediating role, more movie exhibitors showing G-rated movies translates into higher opening week box office revenue. This finding is consistent with the results of previous studies such as Ravid (1999), which shows that G-rated movies on average generate better box office sales than other movies.

7) $DISTRIBUTOR_j$: Apparently, some distributors are doing a better job in attracting theaters than the base case, Disney. However, except for the fact that 20th century Fox and Warner Brothers/New Line are consistently the most effective distributors in managing their "push" strategy, the effects of other major or non-major distributors (including Disney) are not statistically different from one another.

8) $SEASON_j$ and $HOLIDAY_j$: As expected, movies released in the summer season of May – August and the holiday season of November – December fared robustly better in opening week

box office revenue than the base case of movies released in the September – October season. Moreover, across all four models, movies opening in a week covering a major U.S. holiday generate higher opening week box office revenues. This is consistent with the notion that the opportunity cost of movie watching is lower during holidays.

7. Further Analysis

It is apparent from the above results that distribution channels play an important role in mediating the productivity of major TV event advertising in general and Super Bowl advertising in particular. What are the implications for marketers? In this section, we discuss two implications using the illustration of the best fit model, M3: log-quadratic-a.

7.1 Marketing Metrics

First, from a marketing accountability perspective, we argue that marketers should measure the effects of major TV event advertising on both distribution channels and consumer demand. In particular, the use of models like M3 would allow marketers to decompose the total effect on sales into the direct and indirect paths. We use M3 to illustrate this decomposition here. Appendix-B contains the elasticity derivation of the other models. We first identify the two parts of the indirect path, the effect of Super Bowl TV advertising on movie exhibitors and the effect of movie exhibitors on opening week box office revenues, using two measures: $e_{\text{SB-THR}}$, the elasticity of *THEATER* with respect to *SUPERBOWL* and $e_{\text{THR-BO}}$, the elasticity of *BO* with respect to *THEATER*.

$$e_{\text{SB-THR}} = \frac{SUPERBOWL}{THEATER} \cdot \frac{\partial THEATER}{\partial SUPERBOWL}$$

$$= \beta_{I,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL} \qquad (4)$$

$$e_{\text{THR-BO}} = \frac{THEATER}{BO} \cdot \frac{\partial BO}{\partial THEATER}$$

$$= \beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2 \qquad (5)$$

We now summarize the total effect of Super Bowl TV advertising on the opening week box office by $e_{\text{SB-BO}}$, the elasticity of *BO* with respect to *SUPERBOWL*:

$$e_{\text{SB-BO}} = \frac{SUPERBOWL}{BO} \cdot \frac{\partial BO}{\partial SUPERBOWL}$$

$$= (\beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2) \cdot \beta_{1,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$+ \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL} \qquad (6)$$

Note that expression (6) can be re-written as:

$$e_{\text{SB-BO}} = e_{\text{THR-BO}} \cdot e_{\text{SB-THR}} + \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL} \qquad (7)$$

While the first term of (7) is the product of the two components of the indirect path, the second term captures the direct path. As an elasticity is interpreted as the percentage change of an endogenous variable when the corresponding exogenous variable changes by one percent, the decomposition of the total effect using (7) would be very intuitive to marketing practitioners.

Similarly, we can also decompose the total effect of another advertising variable, TV advertising expenditure other than Super Bowl up to but not including the release week, $TVAD_{-1}$, using M3. First, we define the elasticity of *THEATER* with respect to $TVAD_{-1}$, $e_{\text{AD-THR}}$:

$$e_{\text{AD-THR}} = \frac{TVAD_{-1}}{THEATER} \cdot \frac{\partial THEATER}{\partial TVAD_{-1}}$$

$$= \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}} \qquad (8)$$

As stated in (1a), the relation between $TVAD_{-1}$ and $TVAD_0$ is additive. We can therefore express the total effect of $TVAD_{-1}$ on BO by $e_{\text{AD-BO}}$, the elasticity of BO with respect to $TVAD_{-1}$:

$$e_{\text{AD-BO}} = \frac{TVAD_{-1}}{BO} \cdot \frac{\partial BO}{\partial TVAD_{-1}}$$

$$= (\beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2) \cdot \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}}$$

$$+ \beta_{2,SB} \cdot \frac{TVAD_{-1}}{\delta + TVAD_0} \qquad (9)$$

Once again, by (5) and (8), we can decompose (9) into the direct and indirect effects:

$$e_{\text{AD-BO}} = e_{\text{THR-BO}} \cdot e_{\text{AD-THR}} + \beta_{2,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_0} \qquad (10)$$

Table-11 reports the above elasticity measures obtained from our movie sample. Note that the above elasticity measures depend primarily on the value of *THEATER*. We therefore compute the elasticity measures at four values of *THEATER* (its mean, 1st quartile, median, and 3rd quartile) and use only means for *SUPERBOWL* and *TVAD*. One may question the robustness of the elasticity measures in relation to the values of *SUPERBOWL* and/or *TVAD*. The answer is: they do not play an important role. As δ is a very small value (we set it at 0.000001), both $\frac{TVAD_{-1}}{\delta + TVAD_{-1}}$ and $\frac{SUPERBOWL}{\delta + SUPERBOWL}$ are very close to one in computation. Although $TVAD_{-1}$ and $TVAD_0$ are not identical, they are not very different and $\frac{TVAD_{-1}}{\delta + TVAD_0}$ is typically close to one as well. When the above fractions are approximately one, the elasticity measures do not depend on *SUPERBOWL* or *TVAD*. In fact, this is a feature of our M3 model, which assumes log-log forms for the effects of the two TV advertising expenditures.

As we can see from Table-11, the elasticity measures of the total effects, $e_{\text{SB-BO}}$ and $e_{\text{AD-BO}}$, can be decomposed into direct and indirect effects. The indirect effects can be further decomposed as $e_{\text{SB-THR}}$ and $e_{\text{THR-BO}}$ or $e_{\text{AD-THR}}$ and $e_{\text{THR-BO}}$. One can see that these elasticity measures summarize well the findings in our model. First, as discussed in the previous section, while the direct effect of Super Bowl TV advertising is statistically different from zero, the direct effect of other TV advertising expenditures is insignificant. Their corresponding elasticity measures decomposed from $e_{\text{SB-BO}}$ and $e_{\text{AD-BO}}$ therefore maintain this result: $e_{\text{SB-BO}}$ but not $e_{\text{AD-BO}}$ is statistically different from zero. Second, essentially equal to $\beta_{1,SB}$ and $\beta_{1,AD}$, $e_{\text{SB-THR}}$ and $e_{\text{AD-THR}}$ preserve the finding that a one percent change of Super Bowl TV advertising cannot generate as large a percentage change on *THEATER* as one percent of other TV advertising expenditures in the launch period. Third, the increasing marginal return of *BO* to *THEATER* can also be seen in $e_{\text{THR-BO}}$ when we evaluate it at different levels of *THEATER*: the higher value of *THEATER* at which we evaluate $e_{\text{THR-BO}}$, the more elastic the response given by *BO*. Furthermore, this increasing marginal return to *THEATER* is very dominant and this effect pattern is preserved in $e_{\text{SB-BO}}$ and $e_{\text{AD-BO}}$. By decomposing the effects into several components, marketing practitioners can thereby understand which causal path is underperforming and which causal path is the critical one driving end results.

7.2 Marginal Analysis: a Counterfactual Illustration

The second implication for marketing practitioners is that they can use models like M3 to improve their decisions. In particular, subject to marketing budget constraints, they can evaluate the marginal effect of each additional dollar spent on one marketing tactic as opposed to the other. To illustrate this idea, we conducted a counterfactual simulation by giving each movie in our sample an additional \$2.2M, which is equal to one spot during the Super Bowl, to spend on either Super Bowl or other TV advertising opportunities. In particular, we use M3 to simulate opening week theater engagement and box office revenue under three scenarios:

Scenario 0: Each movie does not spent the additional \$2.2M on either Super Bowl or other TV advertising. (This is used as the benchmark for comparison).

Scenario 1: Each movie spends its additional \$2.2M on Super Bowl advertising

Scenario 2: Each movie spends its additional \$2.2M on other TV advertising opportunities.

When using M3 to obtain the predicted values of *THEATER* and *BO* for each movie, we insert the point estimates of individual parameters for the observed exogenous variables. More importantly, we also add the estimates of ε_1 and ε_2 to the simulated values such that the values are identical to the observed values under the benchmark case. Figure-10a and 10b show the simulated values of the two endogenous variables, *THEATER* and *BO*, under different scenarios. While the averages of the simulated values of *THEATER* and *BO* across 398 movies under Scenarios 1 and 2 are higher than the benchmark case, the values under Scenario 1 are highest. At first glance, this simulation result may look inconsistent with our previous finding that Super Bowl TV advertising is not as effective as other TV advertising opportunities. However, as the \$2.2M is added on top of each movie's original advertising plan, which spends on average US\$8M on $TVAD_{-1}$ but zero on *SUPERBOWL*, the marginal effect of *SUPERBOWL* is indeed larger than the marginal effect of $TVAD_{-1}$ in most cases. Therefore, when $TVAD_{-1}$ is in the more saturated region, an additional \$2.2M spent during the Super Bowl event could give more bang than other TV advertising opportunities. This reinforces our earlier argument that Super Bowl advertising presents a good advertising opportunity.

Figure-10c and 10d show a breakdown of the overall means by the groups of Super Bowl-advertised (SB) movies and non-Super Bowl-advertised (NSB) movies. We can see that NSB movies, which have not used Super Bowl TV advertising, can get more impact on

THEATER and *BO* by adopting the Super Bowl TV advertising tactic. On the other hand, as SB movies have already placed at least one spot in the Super Bowl TV event, they receive only a positive but much diminished response if purchasing another spot. SB movies would therefore find spending on other TV advertising opportunities more attractive.

In practice, marketing practitioners evaluate the marginal effects of spending on Super Bowl and other TV advertising opportunities by directly using our models as the market response functions. Figure-11a and 11b plot the response functions of *THEATER* with respect to *SUPERBOWL* and $TVAD_{-1}$ for a base case movie (G-rated family movies distributed by Disney) with *LEAD*, *BUDGET*, *BUZZ* and *PUB* at their means as they appear in our sample. $TVAD_{-1}$ in Figure-11a and *SUPERBOWL* in Figure-11b were kept at their mean values respectively. As we can see, the slope of the response function to *SUPERBOWL* is relatively flat after the jump from zero to one million.[9] On the other hand, the slope of the response function to $TVAD_{-1}$ tends to be larger, although decreasing as $TVAD_{-1}$ increases. We now consider the overall effect of the two advertising tactics. Figure-11c and 11d plot the overall response functions of *BO* with respect to *SUPERBOWL* and $TVAD_{-1}$ for a base case movie at mean *LEAD*, *BUDGET*, *BUZZ*, *PUB* and *CRITICS*. $TVAD_{-1}$ in Figure-11c and *SUPERBOWL* in Figure-11d were kept at their mean values respectively. Note that these response functions contain both direct and indirect effects. As the second part of the indirect path is the response of *BO* to *THEATER*, the overall effect is highly influenced by this mediating factor. Figure-11e plots the response of *BO* to this mediating factor when *SUPERBOWL* and $TVAD_{-1}$ are kept at their mean values. The increasing marginal return pattern after the critical point of 1,041 exhibitors is apparent in the figure. Although the response of *THEATER* to *SUPERBOWL* is rather modest (Figure-11a), the increasing marginal return of *THEATER* clearly magnifies this indirect effect and demonstrates a more apparent

[9] Note that there is little variation of *SUPERBOWL* in our data set. The response function to *SUPERBOWL* is therefore for illustration purposes only.

effect on *BO* (Figure-11c). On the other hand, *THEATER* is already very responsive to $TVAD_{-1}$ (Figure-11b). Combining the increasing marginal return pattern of *THEATER* with this variable actually makes the overall effect of $TVAD_{-1}$ on *BO* exhibit the same increasing marginal return pattern.

8. Concluding Remark

Using a movie sample from the years 2000-2002, this essay demonstrates that Super Bowl TV advertising influences opening week box office revenue through increasing the number of movie exhibitors. This finding is robust to various model specifications. Although Super Bowl TV advertising is not as effective as other launch TV advertising opportunities when both are evaluated at the same levels, Super Bowl TV advertising is still an attractive advertising opportunity in most cases. We hope the essay can attract more attention to the important mediating role of distribution channels in the marketing productivity literature and demonstrate to marketing practitioners how such a crucial mediating factor can be summarized as elasticity measures and used in their marginal analysis.

We acknowledge several limitations in the essay and believe these limitations open interesting research opportunities. First, our study is essentially a cross-sectional analysis. While we can demonstrate how movie exhibitors and potential moviegoers respond to movies that use different advertising tactics, it is not clear whether the response patterns would hold if a movie varied its advertising tactics. Future studies of distribution channels' mediating role may consider panel data, which allows researchers to identify both cross-sectional and longitudinal effects.

Second, there is little variation in terms of Super Bowl TV advertising expenditures within the Super Bowl-advertised movies. We are therefore limited in the ability to distinguish different functional forms of the variables using the data. Future research on Super Bowl TV advertising may consider other product categories, in which one company may place multiple units of TV commercials in the Super Bowl time slot. However, we can foresee that those industries would be faced with the problem of insufficient number of observations, over which the movie industry actually has an advantage.

Third, focusing on the behaviors of movie exhibitors and moviegoers in the opening week, this essay essentially assumes away the dynamic aspect of the advertising decisions. In particular, the feedback mechanism of box office revenues on both exhibitors and moviegoers creates a very challenging future research problem. Fourth, we may study in detail the relation between pre-launch advertising efforts and pre-launch buzz and/or study the evolution of buzz over time. Fifth, our research assumes that there are no strategic behaviors at the level of movie studios (would they increase advertising expenditures if a strong movie is going to open in the same week?) or at the levels of exhibitors (when would movie exhibitors allow double booking of a movie?). Further research in these directions would be challenging but potentially rewarding. Sixth, by summing advertising expenditures over all weeks before the release week, the essay assumes implicitly that there is no decay of the earlier advertising efforts and no interaction between earlier and later advertising. Future research should start relaxing these assumptions.

9. References:

Baron, Reuben M. and David A. Kenny (1986), "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations," *Journal of Personality and Social Psychology*, 51(6), 1173-1182

Chu, Wujin (1992), "Demand Signalling and Screening in Channels of Distribution," *Marketing Science*, 11(4), 327-347

Desai, Preyas S. (2000), "Multiple Messages to Retain Retailers: Signaling New Product Demand," *Marketing Science*, 19(4), 381-389

DeVany, Arthur S. and W. David Walls (1997), "The Market for Motion Pictures: Rank, Revenues, and Survival," *Economic Inquiry*, 4(35), 783-797

Einav, Liran (2003), "Gross Seasonality and Underlying Seasonality: Evidence from the U.S. Motion Picture Industry," working paper, Stanford University

Elberse, Anita and Jehoshua Eliashberg (2003), "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The case of Motion Pictures," *Marketing Science*, 22(3), 329-354

Farris, Paul, James Olver and Cornelis De Kluyver (1989), "The Relationship between Distribution and Market Share," *Marketing Science*, 8(2), 107-132

Gasmi, F., J.J. Laffont, and Q. Vuong (1992), "Econometric Analysis of Collusive Behavior in a Soft-Drink Market," *Journal of Economics & Management Strategy*, 1(2), 277-311

Greene, William H., (2000) *Econometric Analysis*, 4th ed., Prentice Hall

Hanssens, Dominique M., Leonard J. Parsons and Randall L. Schultz (2003), *Market Response Models: Econometric and Time Series Analysis*, 2nd ed., Kluwer Academic Publishers

Jones, J. Morgan, and Christopher J. Ritz (1991), "Incorporating distribution into new product diffusion models," *International Journal of Research in Marketing*, 8, 91-112

Kanner, Bernice (2004), *The Super Bowl of Advertising: How the Commercials won the Game*, Bloomberg Press, Princeton

Krider, Robert E. and Charles B. Weinberg (1998), "Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game," *Journal of Marketing Research*, 35(1), 1-15

Mantrala, Murali K., Prabhakant Sinha, and Andris A. Zoltners (1992), "Impact of Resource Allocation Rules on Marketing Investment-level Decisions and Profitability," *Journal of Marketing Research*, 29(May), 162-175

McElroy, M, (1977), "Goodness of Fit for Seemingly Unrelated Regressions: Glahn's $R^2_{y,x}$ and Hooper's r^2," *Journal of Econometrics*, 6, 381-387

Nail, Jim (2005), *Where is Marketing Measurement Headed?* January 13, 2005, Forrester Research Inc.

Neelamegham, Ramya, and Pradeep Chintagunta (1999), "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets," *Marketing Science*, 18(2), 115-136

Nelson, P. (1970), "Information and Consumer Behavior," *Journal of Political Economy*, 78, 311-329

Newell, Stephen J. and Kenneth V. Henderson (1998), "Super Bowl advertising: field testing the importance of advertisement frequency, length and placement on recall," *Journal of Marketing Communications*, 4, 237-248

Newell, Stephen J. and Kenneth V. Henderson (2001), "The Effects of Pleasure and Arousal on Recall of Advertisements during the Super Bowl," *Psychology and Marketing*, 18, 1135-1153

Niraj, Rakesh, Mahendra Gupta, and Chakravarthi Narasimhan (2001), "Customer Profitability in a Supply Chain," *Journal of Marketing*, 65 (July), 1-16

Parsons, Leonard (1974), "An Econometric Analysis of Advertising, Retail Availability, and Sales of A New Brand," *Management Science*, 20(6), 938-947

Ravid, S. Abraham (1999), "Information, Blockbusters, and Starts," *Journal of Business*, 72, 463-492

Reibstein, David and Paul W. Farris (1995), "Market Share and Distribution: a Generalization, a Speculation, and some Implications," *Marketing Science*, 14(3, part 2 of 2), G190-G202

Reinartz, Werner and V. Kumar (2000), "On the Profitability of Long Lifetime Customers: An Empirical Investigation and Implications for Marketing," *Journal of Marketing*, 64 (October), 17-35

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing*, 68 (October), 76-89

Rust, Roland T., Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (January), 109-127

Sawhney, Mohanbir S. and Jehoshua Eliashberg (1996), "A parsimonious model for forecasting gross box-office revenues of motion pictures," *Marketing Science*, 15(2), 113-131

Srivastava, Rajendra K., Tasadduq A. Shervani and Liam Fahey (1998), "Market-based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (January), 2-18

Srivastava, Rajendra K., Tasadduq A. Shervani and Liam Fahey (1999), "Marketing, Business Processes, and Shareholder Value: An Organizationally Embedded View of Marketing Activities and the Discipline of Marketing," *Journal of Marketing*, 63 (Special Issue), 168-179

Swami, Sanjeev, Jehoshua Eliashberg and Charles B. Weinberg (1999), "SilverScreener: A Modeling Approach to Movie Screens Management," *Marketing Science*, 18(3), 352-372

Tomkovick, Chuck, Rama Yelkur and Lori Christians (2001), "The USA's biggest marketing event keeps getting bigger: an in-depth look at Super Bowl advertising in the 1990s," *Journal of Marketing Communications*, 7, 89-108

Vakratsas, Demetrios, Fred M. Feinberg, Frank M. Bass, and Gurumurthy Kalyanaram (2004), "The Shape of Advertising Response Functions Revisited: A Model of Dynamic Probabilistic Thresholds," *Marketing Science*, 23(1), 109-110

Vuong, Quang H. (1989), "Likelihood Ratio Tests for Model Selection and Non-nested Hypotheses," *Econometrica*, 57(2), 307-333

Yelkur, Rama, Chuck Tomkovick and Patty Traczyk (2004), "Super Bowl Advertising Effectiveness: Hollywood Finds the Games Golden," *Journal of Advertising Research*, March, 143-159

"NBC decides It Can't Live Without Football," *New York Times*, Apr 20, 2005

"A February to Remember for TV and Marketers," *New York Times*, Feb 10, 2005

"Making Marketing Measure up", *BusinessWeek*, Dec 13, 2004

"Big Ticket: Why a commercial during the Super Bowl is worth an unprecedented $80,000 a second," *Broadcasting and Cable*, Jan 31, 2005

"Great value at $80,000 per second," *Advertising Age*, Jan 31, 2005

"The Dysfunctional Family-film Business," *Fortune*, Jan 10, 2005

Appendix-A: Derivation of $BUZZ_j$ from MOVIEmeter™

Since $MOVIEmeter^{TM}$ appears as a rank measure of individual movies' total pageviews in a specific calendar week, it does not immediately allow comparison among different weeks. For example, there are more than a dozen movie titles in our sample having the number one $MOVIEmeter^{TM}$ rank in their release weeks. However, the underlying numbers of visits responsible for these twelve number one ranks are not likely to be the same and therefore these number one ranks may represent different levels of buzz. To make $MOVIEmeter^{TM}$ ranks more compatible across different calendar weeks, we use additional assumptions and data sources to convert the rank measure into a traffic-based measure, $BUZZ_{w,j}$:

$$BUZZ_{w,j} \equiv \frac{1}{MM\_Rank_{w,j} + C} \cdot IMDb\_TRAFFIC_w \qquad \text{(A1)}$$

where $MM\_Rank_{w,j}$ = MOVIEmeter™ rank for movie j in the calendar week w

$IMDb\_TRAFFIC_w$ = Number of visits to *IMDb.com* in the calendar week w

As we do not observe the underlying distribution of the number of visits to a specific movie's page within *IMDb.com*, we have to develop a model to estimate the relation between the rank of a movie and its share of total visitors within week w. The first part of expression (A1) is our assumption for such a relation. C is set at 210 in our data sample, which ensures the sum of $\frac{1}{MM\_Rank_{w,j} + C}$ from the movie of rank 1 to the movie of rank 100, which is the 90 percentile in 398-movie sample, to be bound by one.[10] Intuitively, if two movies have two consecutive ranks in $MOVIEmeter^{TM}$, say m and m+1, we assume the ratio of their numbers of visits to be $\frac{m+C+1}{m+C}$. This ratio will become very close to one if the movies have a very low rank (i.e. large m; relatively few "hits"). This means that when two movies are high in rank,

[10] We have estimated the models with C equal to other values, e.g., $C = 60$, and the results are qualitatively similar to those of $C = 210$.

their difference in numbers of visits could be large. However, when two movies are very low in rank, there is not a large difference between the numbers of visits.

As stated in (A1), if we observe the actual total number of visits to *IMDb.com*, $IMDb\_TRAFFIC_w$, multiplying the above share expression to it would give us the estimated number of visits to a specific movie's page within *IMDb.com*. However, the weekly number of visits to *IMDb.com* is not available. To estimate $IMDb\_TRAFFIC_w$, we use the web behaviors of *Alexa* tool bar users. In particular, we proceed in two steps. First, we estimate the total number of *Alexa* tool bar users in each month, $ALEXA_m$. This is because *Alexa* provides only the daily number of visitors to *IMDb.com* per one million *Alexa* tool bar users (as opposed to the absolute daily number), and the total number of *Alexa* tool bar users is also unavailable. Second, with estimated $ALEXA_m$, we construct a time series of the daily numbers of *Alexa* tool bar users visiting *IMDb.com* from September 2001 to August 2004. This time series then allows us to extrapolate backwards and estimate $IMDb\_TRAFFIC_w$ for the time frame of our data sample.

We now describe the first step in detail. From *internetworldstats.com*, a website archiving internet usage data, we obtained monthly numbers of internet users for some of the months from 2001 to December 2004. As the monthly numbers are available only for some months, we use a regression model to identify the underlying structure of the monthly internet user numbers, $USER_m$:

$$USER_m = \alpha_0 + \alpha_1 \cdot TREND_m + \varepsilon_m, \qquad \text{(A2)}$$

where $TREND_m$ is a monthly trend variable

With 12 observations, we estimated (A2) by OLS and the estimates for α_0 and α_1 are 519.51 (std. error = 9.03) and 8.12 (std. error = 0.41). Inserting these estimates to (A2), we estimated the number of internet users in each month from September 2001 to August 2004, the time frame of *Alexa*'s per million user data. To use a monthly series of $USER_m$ to estimate $ALEXA_m$, we assume that the proportion of *Alexa* users to total number of internet users is fixed over time. As the fixed proportion is just a linear scaling to our final variable, $BUZZ_{w,j}$, we simply set $ALEXA_m = USER_m$.

While the public can access graphs plotting the daily number of visitors to popular websites, like *IMDb.com*, per million *Alexa* tool bar users from September 2001 to August 2004, *Alexa* does not provide the actual numerical values of the data points. Therefore, the second step starts with converting a graph of daily number of *IMDb.com* visitors per million *Alexa* tool bar users to a time series of numerical values. Note that this graph-number conversion procedure makes us unable to obtain all the numerical values from September 2001 to August 2004. In other words, daily values for some dates are missing. Figure-A1 is a graph based on the "reconstructed" daily values. By assuming that the daily number of Alexa users is equal to $ALEXA_m$ if the date falls in month m, we multiply the estimated $ALEXA_m$ by the reconstructed daily values to obtain the daily number of *Alexa* tool bar users visiting *IMDb.com*, $IMDb\_ALEXA_d$. In order to interpolate and extrapolate $IMDb\_ALEXA_d$ for all weeks in our sampling frame of 2000-2002, we identify the underlying seasonality and time trend using the regression model:

$$\begin{aligned} \ln(IMDb\_ALEXA_d) = \gamma_0 &+ \gamma_1 \cdot TREND_w \\ &+ \gamma_2 \cdot FEB + \gamma_3 \cdot MAR + \ldots + \gamma_{13} \cdot DEC \\ &+ \gamma_{14} \cdot NEWYEAR + \ldots + \gamma_{23} \cdot XMAS + \varepsilon_m, \end{aligned} \tag{A3}$$

where $TREND_w$ is a weekly trend variable

FEB, MAR, …, DEC are 11 binary variables to indicate if date d is in the week of February, March, … or December (January is used as the base case)

NEWYEAR, …, XMAS are 10 binary variables to indicate if date d is in the week containing the holiday of New Year, Martin Luther King Day, Presidents Day, Memorial

Day, Independence Day, Labor Day, Columbia Day, Veterans Day, Thanksgiving or Christmas.

Model (A3) is estimated with 180 observations. Table-A1 presents the estimation results. While the trend and several monthly binaries are significant, the holiday binary variables turn out to have large standard errors. We speculate that this is due to the limited number of observations with the specific holidays (only three years of data) and believe the holiday binaries still capture some seasonality of *IMDb.com* traffic. We therefore use (A3) to estimate the number of *Alexa* users visiting *IMDb.com* for 2000-2002. In particular, two adjustments are made when interpolating/extrapolating $IMDb\_ALEXA_d$. First, as (A3) is a log-linear model, a correction factor for the downward bias is used. The details of the correction factor can be found in Hanssens, Parsons and Schultz (2003), p.395. Second, $TREND_w$ is set to zero, essentially de-trending the traffic of *IMDb.com* while keeping the seasonality across weeks.

Note that $MM\_Rank_{w,j}$, from which we are deriving $BUZZ_{w,j}$, is a weekly measure. We therefore only need to generate weekly, rather than daily, numbers of *Alexa* users visiting *IMDb.com*. By assuming the daily number of *Alexa* users to be constant across different days of a week, the weekly number of *Alexa* users visiting *IMDb.com*, $IMDb\_ALEXA_w = 7*IMDb\_ALEXA_d$, if date d falls into week w. As seven is just a linear scaling to our ultimate variable of interest, $BUZZ_{w,j}$, we can simply set $IMDb\_ALEXA_w$ equal to $IMDb\_ALEXA_d$, for date d falls into week w. Also note that our definition of "week" here is consistent with the definition of "week" used by *IMDb.com* for their *MOVIEmeter*™, which starts Monday and ends on the following Sunday.

The last assumption we must make concerns the relation between $IMDb\_ALEXA_w$ and $IMDb\_TRAFFIC_w$. By assuming that the proportion of *Alexa* users visiting *IMDb.com* to all visitors of *IMDb.com* is constant over time and that each visitor makes the same number of visits to *IMDb.com* in each week, we can argue that $IMDb\_ALEXA_w$ is related to $IMDb\_TRAFFIC_w$ by a fixed proportion and we can therefore set $IMDb\_TRAFFIC_w = IMDb\_ALEXA_w$. Finally, we use expression (A1) to generate $BUZZ_{w,j}$ for movie j in its release week and a week before the release. For ease of estimation, we scaled $BUZZ_{w,j}$ by million.

In addition to the above formulation of $BUZZ_{w,j}$, we have also tried 1/ (*MOVIEmeter*™ rank) as an alternative formulation of $BUZZ_{w,j}$. As the main results are similar to those obtained from the above procedure, we report only the latter.

Appendix-B: Elasticity Measures based on M1-M4

Five elasticity measures can be derived from each of M1-M4:

Elasticity of *THEATER* w.r.t. *SUPERBOWL*, $e_{\text{SB-THR}} = \dfrac{SUPERBOWL}{THEATER} \cdot \dfrac{\partial THEATER}{\partial SUPERBOWL}$ (B1)

Elasticity of *THEATER* w.r.t. $TVAD_{-1}$, $e_{\text{AD-THR}} = \dfrac{TVAD_{-1}}{THEATER} \cdot \dfrac{\partial THEATER}{\partial TVAD_{-1}}$ (B2)

Elasticity of *BO* w.r.t. *THEATER*, $e_{\text{THR-BO}} = \dfrac{THEATER}{BO} \cdot \dfrac{\partial BO}{\partial THEATER}$ (B3)

Elasticity of *BO* w.r.t. *SUPERBOWL*, $e_{\text{SB-BO}} = \dfrac{SUPERBOWL}{BO} \cdot \dfrac{\partial BO}{\partial SUPERBOWL}$ (B4)

Elasticity of *BO* w.r.t. $TVAD_{-1}$, $e_{\text{AD-BO}} = \dfrac{TVAD_{-1}}{BO} \cdot \dfrac{\partial BO}{\partial TVAD_{-1}}$ (B5)

M1: Log-linear Model

By the first order derivatives of (2a) and (3a) with respect to *SUPERBOWL* and $TVAD_{-1}$, we can obtain the following elasticity measures:

$e_{\text{SB-THR}} = \beta_{1,SB} \cdot SUPERBOWL$

$e_{\text{AD-THR}} = \beta_{1,AD} \cdot TVAD_{-1}$

$e_{\text{THR-BO}} = \beta_{THR} \cdot THEATER$

$e_{\text{SB-BO}} = \beta_{THR} \cdot THEATER \cdot \beta_{1,SB} \cdot SUPERBOWL + \beta_{2,SB} \cdot SUPERBOWL$

$= e_{\text{THR-BO}} \cdot e_{\text{SB-THR}} + \beta_{2,SB} \cdot SUPERBOWL$

$e_{\text{AD-BO}} = \beta_{THR} \cdot THEATER \cdot \beta_{1,AD} \cdot TVAD_{-1} + \beta_{2,AD} \cdot TVAD_{-1}$

$= e_{\text{THR-BO}} \cdot e_{\text{AD-THR}} + \beta_{2,AD} \cdot TVAD_{-1}$

M2: Log-Log Model

By the first order derivatives of (2b) and (3b) with respect to *SUPERBOWL* and $TVAD_{-1}$, we can obtain the following elasticity measures:

$$e_{\text{SB-THR}} = \beta_{1,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$e_{\text{AD-THR}} = \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}}$$

$$e_{\text{THR-BO}} = \beta_{THR}$$

$$e_{\text{SB-BO}} = \beta_{THR} \cdot \beta_{1,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL} + \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$= e_{\text{THR-BO}} \cdot e_{\text{SB-THR}} + \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$e_{\text{AD-BO}} = \beta_{THR} \cdot \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}} + \beta_{2,AB} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{0}}$$

$$= e_{\text{THR-BO}} \cdot e_{\text{AD-THR}} + \beta_{2,AB} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{0}}$$

M3 & M4: Log-Quadratic

$$e_{\text{SB-THR}} = \beta_{1,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$e_{\text{AD-THR}} = \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}}$$

$$e_{\text{THR-BO}} = \beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2$$

$$e_{\text{SB-BO}} = (\beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2) \cdot \beta_{1,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$+ \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$= e_{\text{THR-BO}} \cdot e_{\text{SB-THR}} + \beta_{2,SB} \cdot \frac{SUPERBOWL}{\delta + SUPERBOWL}$$

$$e_{\text{AD-BO}} = (\beta_{THR1} \cdot THEATER + 2 \cdot \beta_{THR2} \cdot THEATER^2) \cdot \beta_{1,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_{-1}}$$

$$+ \beta_{2,SB} \cdot \frac{TVAD_{-1}}{\delta + TVAD_0}$$

$$= e_{\text{THR-BO}} \cdot e_{\text{AD-THR}} + \beta_{2,AD} \cdot \frac{TVAD_{-1}}{\delta + TVAD_0}$$

Table-1: Summary of Variables

BO_j	≡	Opening week box office revenues by movie *j*
$THEATER_j$	≡	Number of movie theaters engaged for movie *j* in the release week
$SUPERBOWL_j$	≡	Super Bowl TV advertising expenditure by movie *j*
$TVAD_{-1,j}$	≡	Total TV advertising expenditure other than $SUPERBOWL_j$, up to and including the week before the release week of movie *j* (i.e. Total launch TV Ad effort, observed by theater managers before their final screening decisions)
$TVAD_{0,j}$	≡	Total TV advertising expenditure other than $SUPERBOWL_j$, up to and including the release week of movie *j* (i.e. Total launch TV Ad effort, observed by potential moviegoers before their moviegoing decisions)
$LEAD_j$	≡	No. of weeks between the first major TV advertising effort and the release week of movie *j*
$BUDGET_j$	≡	Production budget (US$) of movie *j*
$BUZZ_{-1,j}$	≡	Buzz for movie *j* in the week before its release week (i.e. The buzz observed by theater managers when making their final screening decisions)
$BUZZ_{0,j}$	≡	Buzz for movie j in its release week (i.e. The buzz generated and observed by the potential moviegoers when making their moviegoing decisions)
$PUB_{-1,j}$	≡	Cumulative Publicity received by movie *j*, up to the release week
$PUB_{0,j}$	≡	Cumulative Publicity received by movie *j*, up to and including the release week
$CRITICS_j$	≡	Average critics rating given for movie *j*
$DISTRIBUTOR_j$	≡	A set of binary variables to indicate if movie *j* is distributed by one of the following distributor groups: 1) Buena Vista or Miramax, 2) Warner Brothers or New Line, 3) Paramount, 4) Sony, 5) 20th Century Fox, 6) Universal, and 7) Other movie distributors
$GENRE_j$	≡	A set of binary variables to indicate if movie *j* is of one of the genre categories: 1) action, 2) comedy, 3) drama, and 4) family
$MPAA_j$	≡	A set of binary variables to indicate if movie *j* is rated by MPAA into one of the following categories: 1) G, 2) PG, 3) PG-13, and 4) R
$SEASON_j$	≡	A set of binary variables to indicate if movie *j* is released in one of the following four Hollywood seasons: 1) January – April, 2) May – August, 3) September – October, and 4) November – December
$HOLIDAY_j$	≡	A binary variable to indicate if movie *j* is released in the week covering any of the following major U.S. holidays: New Year, Martin Luther King Day, Presidents Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas

Table-2: MPAA Member Company Distribution of Advertising Costs by Media

Year	Newspaper	TV	Internet /Online	Trailers	Other Media
2003	17.29%	48.38%	1.62%	5.47%	27.24%
2002	16.69%	50.19%	1.11%	5.56%	26.45%
2001	15.98%	51.59%	1.59%	6.22%	24.63%
2000	18.66%	50.36%	0.84%	7.66%	22.49%
1999	20.80%	51.18%	0.59%	9.22%	18.20%

Table-3: List of Super Bowl Movies

Movie Title	Release Week	Total Box Office Revenues (US$ in Million)	Opening week Box Office Revenues (US$ in Million)	Number of Theaters engaged in the opening week (in Thousand)	Super Bowl TV advertising Expenditure (US$ in Million)	Other TV advertising Expenditure before the opening week (US$ in Million)	Other TV advertising Expenditure before and including the opening week (US$ in Million)
Gladiator (Dreamworks)	5/5/2000	187.7	49.0	2.938	2.1	12.8	17.6
Mission to Mars (Buena Vista)	3/10/2000	60.9	29.2	3.054	4.2	10.2	13.1
Nutty Professor 2: The Klumps (Universal)	7/28/2000	123.3	58.5	3.242	2.1	9.0	12.9
Titan A.E. (20th C Fox)	6/16/2000	22.8	13.2	2.734	2.1	11.8	14.6
U-571 (Universal)	4/21/2000	77.1	25.9	2.583	2.1	7.9	12.0
A Knight's Tale (Sony)	5/11/2001	56.1	21.5	2.980	2.2	11.6	15.3
Exit Wounds (WB)	3/16/2001	51.8	23.4	2.830	2.2	6.5	9.3
Hannibal (MGM/UA)	2/9/2001	165.1	73.9	3.230	2.2	10.0	14.0
Swordfish (WB)	6/8/2001	69.8	27.1	2.678	2.2	13.3	17.1
The Mummy Returns (Universal)	5/4/2001	202.1	84.3	3.401	2.2	12.2	19.9
40 Days and 40 Nights (Mira Max)	3/1/2002	38.0	15.8	2.225	2.2	8.0	10.6
Austin Powers in Goldmember (New Line)	7/26/2002	213.1	110.6	3.613	2.2	9.4	14.5
Bad Company (Buena Vista)	6/7/2002	30.2	15.7	2.944	2.2	13.2	17.0
Blade 2 (New Line)	3/22/2002	81.7	41.9	2.707	2.2	5.7	8.5
Collateral Damage (WB)	2/8/2002	40.1	19.5	2.824	2.2	13.5	16.4
Hart's War (MGM/UA)	2/15/2002	19.1	10.5	2.459	2.2	11.3	17.0
Signs (Buena Vista)	8/2/2002	228.0	88.3	3.264	2.2	7.8	10.4
The Scorpion King (Universal)	4/19/2002	90.5	43.3	3.444	2.2	9.4	13.4
XXX (Sony)	8/9/2002	141.2	61.9	3.374	2.2	15.7	20.5

Table-3 (Continued): List of Super Bowl Movies

Movie Title	Time Lag from Super Bowl to the Release Week	Time Lag from the first major TV advertising effort and the Release Week	Production Budget (US$ in Million)	Buzz in the week before the Release week	Buzz in the week during the Release week	Publicity received before and including the Release week	Average Critics Rating	Genre	MPAA Rating
Gladiator (Dreamworks)	14	14	103	0.0278	0.0281	7.2	7	Drama	R
Mission to Mars (Buena Vista)	6	6	90	0.0276	0.0276	1.2	4.1	Action	PG
Nutty Professor 2: The Klumps (Universal)	26	26	84	0.0279	0.0279	4.0	4.4	Comedy	PG13
Titan A.E. (20th C Fox)	20	20	75	0.0268	0.0269	1.2	5.7	Family	PG
U-571 (Universal)	12	12	62	0.0278	0.0278	5.2	6.3	Action	PG13
A Knight's Tale (Sony)	15	15	41	0.0022	0.0063	5.2	5.7	Action	PG13
Exit Wounds (WB)	7	7	33	0.0266	0.0273	0.0	4.3	Action	R
Hannibal (MGM/UA)	2	4	87	0.0296	0.0296	21.7	5	Drama	R
Swordfish (WB)	19	19	80	0.0267	0.0272	1.2	4.4	Action	R
The Mummy Returns (Universal)	14	14	98	0.0278	0.0281	9.2	5.2	Action	PG13
40 Days and 40 Nights (Mira Max)	4	4	17	0.0251	0.0272	1.2	4.9	Comedy	R
Austin Powers in Goldmember (New Line)	25	25	63	0.0279	0.0287	13.5	5.8	Comedy	PG13
Bad Company (Buena Vista)	18	39	70	0.0227	0.0262	0.0	3.9	Action	PG13
Blade 2 (New Line)	7	7	55	0.0262	0.0273	1.2	5.8	Action	R
Collateral Damage (WB)	1	22	85	0.0254	0.0291	0.5	4	Action	R
Hart's War (MGM/UA)	2	3	70	0.0269	0.0287	1.2	5.9	Drama	R
Signs (Buena Vista)	26	26	72	0.0282	0.0275	3.2	6.9	Drama	PG13
The Scorpion King (Universal)	11	11	60	0.0259	0.0276	3.2	4.8	Action	PG13
XXX (Sony)	27	27	85	0.0264	0.0273	10.0	5.6	Action	PG13

Table-4: Classification of *Entertainment Weekly* Articles for PUB_j operationalization

Article Type	Average page number
News & Notes Category I	6
News & Notes Category II	4
News & Notes Category III	2
News & Notes Category IV	1
News & Notes Category V	0.8
Special Preview Feature	2
Departments	1.25
Movie Review	1.2
Internet Page	0.5
Mail Page	0.25

Table-5: Pearson Correlation Matrix of continuous variables (Sample Size = 398)

	BO_j	$THEATER_j$	$SUPER\ BOWL_j$	$TVAD_{-1,j}$	$TVAD_{0,j}$	$LEAD_j$	$BUDGET_j$	$CRITICS_j$	$BUZZ_{-1,j}$	$BUZZ_{0,j}$	$PUB_{-1,j}$	$PUB_{0,j}$
BO_j	1.000	0.637	0.209	0.498	0.514	0.364	0.631	0.405	0.135	0.134	0.608	0.688
$THEATER_j$	0.637	1.000	0.204	0.675	0.705	0.379	0.631	0.190	0.186	0.234	0.320	0.396
$SUPERBOWL_j$	0.209	0.204	1.000	0.108	0.120	0.419	0.201	0.029	0.052	0.054	0.091	0.116
$TVAD_{-1,j}$	0.498	0.675	0.108	1.000	0.974	0.370	0.690	0.331	0.160	0.234	0.268	0.337
$TVAD_{0,j}$	0.514	0.705	0.120	0.974	1.000	0.358	0.689	0.356	0.167	0.238	0.264	0.338
$LEAD_j$	0.364	0.379	0.419	0.370	0.358	1.000	0.317	0.120	-0.001	0.063	0.135	0.182
$BUDGET_j$	0.631	0.631	0.201	0.690	0.689	0.317	1.000	0.294	0.160	0.174	0.404	0.485
$CRITICS_j$	0.405	0.190	0.029	0.331	0.356	0.120	0.294	1.000	0.010	0.048	0.288	0.350
$BUZZ_{-1,j}$	0.135	0.186	0.052	0.160	0.167	-0.001	0.160	0.010	1.000	0.883	0.100	0.109
$BUZZ_{0,j}$	0.134	0.234	0.054	0.234	0.238	0.063	0.174	0.048	0.883	1.000	0.079	0.087
$PUB_{-1,j}$	0.608	0.320	0.091	0.268	0.264	0.135	0.404	0.288	0.100	0.079	1.000	0.908
$PUB_{0,j}$	0.688	0.396	0.116	0.337	0.338	0.182	0.485	0.350	0.109	0.087	0.908	1.000

Table-6: Summary Statistics of non-Super Bowl vs. Super Bowl advertised movies

Variables	Group	Mean	Std. Deviation	Minimum	Maximum
BO_j ($ in Millions)	Non-Super bowl	20.17	21.13	0.76	151.62
	Super bowl	42.81	28.54	10.54	110.56
$THEATER_j$ (in Thousands)	Non-Super bowl	2.30	0.69	0.60	3.68
	Super bowl	2.97	0.36	2.23	3.61
$TVAD_{-1,j}$ ($ in Millions)	Non-Super bowl	8.32	4.19	0.06	20.80
	Super bowl	10.48	2.60	5.69	15.75
$TVAD_{0,j}$ ($ in Millions)	Non-Super bowl	11.52	5.03	0.21	23.98
	Super bowl	14.44	3.29	8.53	20.53
$LEAD_j$	Non-Super bowl	5.03	4.19	0.00	34.00
	Super bowl	15.84	9.63	3.00	39.00
$BUDGET_j$ ($ in Millions)	Non-Super bowl	40.70	31.15	1.00	142.00
	Super bowl	70.00	21.51	17.00	103.00
$BUZZ_{-1,j}$	Non-Super bowl	0.024	0.006	0.000	0.034
	Super bowl	0.026	0.006	0.002	0.030
$BUZZ_{0,j}$	Non-Super bowl	0.025	0.006	0.000	0.035
	Super bowl	0.027	0.005	0.006	0.030
$PUB_{-1,j}$	Non-Super bowl	1.34	3.02	0.00	30.60
	Super bowl	2.84	5.07	0.00	20.50
$PUB_{0,j}$	Non-Super bowl	2.43	3.73	0.00	31.55
	Super bowl	4.74	5.43	0.00	21.70
$CRITICS_j$	Non-Super bowl	5.00	1.36	2.20	9.20
	Super bowl	5.25	0.91	3.90	7.00

Table-7: Frequency of non-Super Bowl vs. Super Bowl advertised movies

		Frequency	Percentage in the sample
By Studio			
Buena Vista/Miramax	Non-Super bowl	65	16%
	Super bowl	4	1%
WB/New Line	Non-Super bowl	86	22%
	Super bowl	5	1%
Paramount	Non-Super bowl	43	11%
	Super bowl	0	0%
Sony	Non-Super bowl	50	13%
	Super bowl	2	1%
20th Century Fox	Non-Super bowl	43	11%
	Super bowl	1	0%
Universal	Non-Super bowl	32	8%
	Super bowl	4	1%
Rest of the Studios	Non-Super bowl	60	15%
	Super bowl	3	1%
By Ratings			
Rating: G	Non-Super bowl	19	5%
	Super bowl	0	0%
Rating: PG	Non-Super bowl	48	12%
	Super bowl	2	1%
Rating: PG13	Non-Super bowl	173	43%
	Super bowl	9	2%
Rating: R	Non-Super bowl	139	35%
	Super bowl	8	2%
By Genre			
Genre: Action	Non-Super bowl	79	20%
	Super bowl	11	3%
Genre: Comedy	Non-Super bowl	146	37%
	Super bowl	3	1%
Genre: Drama	Non-Super bowl	122	31%
	Super bowl	4	1%
Genre: Family	Non-Super bowl	32	8%
	Super bowl	1	0%

Table-7 (Continued): Frequency of non-Super Bowl vs. Super Bowl advertised movies

		Frequency	Percentage in the sample
By Hollywood Seasons			
January – April	Non-Super bowl	120	30%
	Super bowl	9	2%
May – August	Non-Super bowl	118	30%
	Super bowl	10	3%
September – October	Non-Super bowl	72	18%
	Super bowl	0	0%
November – December	Non-Super bowl	69	17%
	Super bowl	0	0%
By Major U.S. Holidays			
Release week covering a major holiday	Non-Super bowl	66	17%
	Super bowl	1	0%
Release week NOT covering any major holiday	Non-Super bowl	313	79%
	Super bowl	18	5%

Table-8: Pairwise tests[11] for non-nested model (Vuong 1989)

Weighted Likelihood Ratio Statistic	M2: log-log	M3: Log-Quadratic-a	M4: Log-Quadratic-b
M1: Log-linear	-0.708	-4.487	-3.197
M2: log-log		-3.743	-3.733
M3: Log-Quadratic-a			1.200

Critical value for 2-tail 5% significance level: 1.960
Critical value for 2-tail 10% significance level: 1.645

[11] Please refer to Gasmi, Laffont and Vuong (1992) for the detailed calculation of the statistics

Table-9a: Parameter Estimates of M1: Log-linear Model

Variable	Two-path Model: Coefficient Estimate	Standard Error	P-value for H: β=0	Single-path Model: Coefficient Estimate	Standard Error	P-value for H: β=0
	Equation: ln($THEATER_j$)			Equation: ln($THEATER_j$)		
Intercept	**0.392**	**0.093**	**0.000**	**0.368**	**0.098**	**0.000**
$SUPERBOWL_j$	**0.051**	**0.019**	**0.007**	**0.051**	**0.019**	**0.006**
$TVAD_{-1,j}$	**0.043**	**0.005**	**0.000**	**0.043**	**0.005**	**0.000**
$BUDGET_j$	**0.002**	**0.001**	**0.010**	**0.001**	**0.001**	**0.008**
$LEAD_j$	0.002	0.002	0.347	0.003	0.002	0.261
$BUZZ_{-1,j}$	**6.344**	**2.585**	**0.014**	**6.778**	**2.683**	**0.012**
$PUB_{-1,j}$	0.006	0.003	0.061	**0.007**	**0.003**	**0.023**
GENRE: Action	-0.050	0.056	0.374	-0.044	0.056	0.434
GENRE: Comedy	**-0.115**	**0.053**	**0.031**	**-0.108**	**0.053**	**0.040**
GENRE: Drama	**-0.143**	**0.058**	**0.013**	**-0.135**	**0.057**	**0.019**
MPAA: PG	-0.132	0.070	0.058	-0.122	0.068	0.072
MPAA: PG13	**-0.160**	**0.071**	**0.024**	**-0.157**	**0.067**	**0.019**
MPAA: R	**-0.180**	**0.075**	**0.016**	**-0.181**	**0.070**	**0.010**
WB/New Line	**0.099**	**0.044**	**0.026**	**0.086**	**0.031**	**0.005**
Paramount	0.081	0.051	0.108	0.074	0.040	0.066
Sony	0.061	0.047	0.196	**0.084**	**0.032**	**0.008**
20th Century Fox	**0.129**	**0.047**	**0.006**	**0.107**	**0.034**	**0.002**
Universal	0.096	0.059	0.102	0.046	0.049	0.342
Other Distributors	-0.051	0.056	0.370	0.007	0.038	0.849
	Equation: ln(BO_j)			Equation: ln(BO_j)		
Intercept	**-0.913**	**0.334**	**0.006**	**0.608**	**0.241**	**0.012**
$THEATER_j$	**0.914**	**0.172**	**0.000**			
$SUPERBOWL_j$	**0.090**	**0.045**	**0.045**	**0.162**	**0.060**	**0.007**
$TVAD_{0,j}$	0.000	0.013	0.978	**0.054**	**0.009**	**0.000**
$BUDGET_j$	-0.002	0.002	0.303	0.003	0.002	0.097
$LEAD_j$	-0.001	0.005	0.814	0.007	0.007	0.342
$BUZZ_{0,j}$	5.657	4.775	0.236	**14.769**	**5.294**	**0.005**
$PUB_{0,j}$	**0.043**	**0.007**	**0.000**	**0.062**	**0.007**	**0.000**
GENRE: Action	**0.271**	**0.140**	**0.052**	0.116	0.113	0.303
GENRE: Comedy	**0.281**	**0.139**	**0.043**	0.019	0.102	0.855
GENRE: Drama	0.257	0.147	0.080	-0.074	0.111	0.506
MPAA: PG	-0.157	0.150	0.296	-0.290	0.155	0.062
MPAA: PG13	-0.057	0.162	0.726	-0.233	0.148	0.115
MPAA: R	-0.040	0.172	0.817	-0.260	0.153	0.089
SEASON: Jan-Apr	0.034	0.065	0.603	0.020	0.070	0.780
SEASON: May-Aug	**0.259**	**0.070**	**0.000**	**0.270**	**0.072**	**0.000**
SEASON: Nov-Dec	**0.166**	**0.083**	**0.046**	0.152	0.085	0.072
$HOLIDAY_j$	**0.188**	**0.068**	**0.006**	**0.173**	**0.069**	**0.012**
$CRITICS_j$	**0.179**	**0.020**	**0.000**	**0.161**	**0.021**	**0.000**
McElroy's R^2	0.700			0.569		
Log-likelihood	-1624.318			-1645.189		
Likelihood Ratio				41.745	(P-value = 0.000)	

Table-9b: Parameter Estimates of M2: Log-Log Model

Variable	Two-path Model: Coefficient Estimate	Standard Error	P-value for H: β=0	Single-path Model: Coefficient Estimate	Standard Error	P-value for H: β=0
	Equation: ln($THEATER_j$)			Equation: ln($THEATER_j$)		
Intercept	**0.495**	**0.149**	**0.001**	**0.422**	**0.151**	**0.005**
ln(δ+$SUPERBOWL_j$)	**0.010**	**0.003**	**0.001**	**0.009**	**0.003**	**0.002**
ln(δ+$TVAD_{-1,j}$)	**0.320**	**0.038**	**0.000**	**0.316**	**0.037**	**0.000**
ln($BUDGET_j$)	**0.069**	**0.022**	**0.002**	**0.081**	**0.022**	**0.000**
ln(δ+$LEAD_j$)	-0.032	0.020	0.107	-0.025	0.021	0.233
ln($BUZZ_{-1,j}$)	0.036	0.021	0.087	**0.041**	**0.021**	**0.053**
ln(δ+$PUB_{-1,j}$)	0.004	0.002	0.140	0.000	0.002	0.979
GENRE: Action	-0.069	0.054	0.196	-0.067	0.049	0.178
GENRE: Comedy	**-0.150**	**0.050**	**0.003**	**-0.144**	**0.044**	**0.001**
GENRE: Drama	**-0.177**	**0.055**	**0.001**	**-0.165**	**0.050**	**0.001**
MPAA: PG	**-0.136**	**0.064**	**0.034**	-0.120	0.068	0.076
MPAA: PG13	**-0.180**	**0.065**	**0.006**	**-0.167**	**0.066**	**0.012**
MPAA: R	**-0.199**	**0.070**	**0.004**	**-0.185**	**0.071**	**0.009**
WB/New Line	**0.124**	**0.048**	**0.009**	**0.111**	**0.029**	**0.000**
Paramount	0.085	0.045	0.057	**0.069**	**0.034**	**0.044**
Sony	**0.105**	**0.047**	**0.025**	**0.099**	**0.029**	**0.001**
20th Century Fox	**0.147**	**0.046**	**0.001**	**0.117**	**0.032**	**0.000**
Universal	0.097	0.059	0.099	0.062	0.048	0.190
Other Distributors	0.007	0.064	0.911	0.047	0.037	0.203
	Equation: ln(BO_j)			Equation: ln(BO_j)		
Intercept	0.330	0.384	0.391	0.711	0.394	0.071
ln($THEATER_j$)	**1.651**	**0.756**	**0.029**			
ln(δ+$SUPERBOWL_j$)	0.018	0.011	0.090	**0.030**	**0.011**	**0.008**
ln(δ+$TVAD_{0,j}$)	-0.189	0.274	0.491	**0.362**	**0.093**	**0.000**
ln($BUDGET_j$)	0.006	0.080	0.938	**0.160**	**0.055**	**0.004**
ln(δ+$LEAD_j$)	0.029	0.027	0.295	0.016	0.051	0.750
ln($BUZZ_{0,j}$)	0.052	0.043	0.230	**0.121**	**0.051**	**0.019**
ln(δ+$PUB_{0,j}$)	**0.021**	**0.004**	**0.000**	**0.021**	**0.005**	**0.000**
GENRE: Action	0.289	0.183	0.114	0.165	0.104	0.112
GENRE: Comedy	0.253	0.203	0.212	-0.005	0.071	0.943
GENRE: Drama	0.210	0.224	0.348	-0.080	0.093	0.391
MPAA: PG	-0.072	0.109	0.508	-0.193	0.167	0.248
MPAA: PG13	-0.008	0.119	0.949	-0.187	0.149	0.211
MPAA: R	-0.036	0.132	0.787	-0.230	0.156	0.142
SEASON: Jan-Apr	-0.023	0.083	0.781	-0.013	0.082	0.878
SEASON: May-Aug	**0.326**	**0.083**	**0.000**	**0.348**	**0.081**	**0.000**
SEASON: Nov-Dec	**0.252**	**0.099**	**0.011**	**0.289**	**0.094**	**0.002**
$HOLIDAY_j$	**0.197**	**0.074**	**0.008**	**0.181**	**0.075**	**0.016**
ln($CRITICS_j$)	**0.975**	**0.102**	**0.000**	**0.927**	**0.103**	**0.000**
McElroy's R^2	0.666			0.519		
Log-likelihood	-1613.544			-1617.683		
Likelihood Ratio				8.283	(P-value = 0.004)	

δ is set to be 0.000001

Table-9c: Parameter Estimates of M3: Log-Quadratic-a Model

	Two-path Model			**Single-path Model**		
Variable	Coefficient Estimate	Standard Error	P-value for H: β=0	Coefficient Estimate	Standard Error	P-value for H: β=0
	Equation: $\ln(THEATER_j)$			Equation: $\ln(THEATER_j)$		
Intercept	0.077	0.114	0.499	0.073	0.121	0.544
$\ln(\delta+SUPERBOWL_j)$	**0.006**	**0.003**	**0.019**	**0.006**	**0.003**	**0.028**
$\ln(\delta+TVAD_{-1,j})$	**0.292**	**0.040**	**0.000**	**0.288**	**0.039**	**0.000**
$\ln(BUDGET_j)$	**0.076**	**0.024**	**0.002**	**0.078**	**0.024**	**0.001**
$LEAD_j$	0.002	0.002	0.389	0.002	0.002	0.317
$BUZZ_{-1,j}$	**6.516**	**2.354**	**0.006**	**6.440**	**2.347**	**0.006**
$PUB_{-1,j}$	**0.007**	**0.003**	**0.017**	**0.007**	**0.003**	**0.009**
GENRE: Action	-0.061	0.053	0.254	-0.059	0.053	0.263
GENRE: Comedy	**-0.131**	**0.050**	**0.008**	**-0.130**	**0.051**	**0.010**
GENRE: Drama	**-0.155**	**0.054**	**0.004**	**-0.154**	**0.055**	**0.005**
MPAA: PG	**-0.140**	**0.066**	**0.036**	**-0.130**	**0.067**	**0.054**
MPAA: PG13	**-0.181**	**0.066**	**0.006**	**-0.172**	**0.066**	**0.009**
MPAA: R	**-0.202**	**0.070**	**0.004**	**-0.192**	**0.070**	**0.006**
WB/New Line	**0.122**	**0.036**	**0.001**	**0.099**	**0.029**	**0.001**
Paramount	**0.079**	**0.041**	**0.052**	0.066	0.035	0.061
Sony	**0.115**	**0.033**	**0.001**	**0.102**	**0.029**	**0.000**
20th Century Fox	**0.135**	**0.045**	**0.003**	**0.118**	**0.031**	**0.000**
Universal	0.075	0.061	0.222	0.049	0.048	0.303
Other Distributors	0.037	0.049	0.447	0.040	0.035	0.244
	Equation: $\ln(BO_j)$			Equation: $\ln(BO_j)$		
Intercept	0.590	0.638	0.355	0.208	0.326	0.523
$THEATER_j$	-0.452	0.743	0.543			
$THEATER_j^2$	**0.217**	**0.101**	**0.032**			
$\ln(\delta+SUPERBOWL_j)$	**0.017**	**0.008**	**0.034**	**0.024**	**0.010**	**0.020**
$\ln(\delta+TVAD_{0,j})$	0.319	0.220	0.147	**0.421**	**0.078**	**0.000**
$\ln(BUDGET_j)$	-0.015	0.068	0.831	**0.109**	**0.051**	**0.033**
$LEAD_j$	0.000	0.006	0.959	0.008	0.007	0.299
$BUZZ_{0,j}$	11.622	6.160	0.059	**15.684**	**5.227**	**0.003**
$PUB_{0,j}$	**0.043**	**0.007**	**0.000**	**0.064**	**0.007**	**0.000**
GENRE: Action	0.245	0.138	0.076	0.120	0.151	0.429
GENRE: Comedy	0.183	0.154	0.235	-0.005	0.154	0.975
GENRE: Drama	0.169	0.168	0.314	-0.095	0.152	0.531
MPAA: PG	-0.263	0.149	0.077	-0.268	0.164	0.102
MPAA: PG13	-0.191	0.161	0.236	-0.218	0.164	0.183
MPAA: R	-0.189	0.169	0.266	-0.253	0.169	0.135
SEASON: Jan-Apr	0.055	0.066	0.410	0.016	0.064	0.801
SEASON: May-Aug	**0.270**	**0.071**	**0.000**	**0.293**	**0.070**	**0.000**
SEASON: Nov-Dec	**0.196**	**0.082**	**0.017**	**0.215**	**0.082**	**0.009**
$HOLIDAY_j$	**0.163**	**0.068**	**0.017**	**0.172**	**0.071**	**0.015**
$CRITICS_j$	**0.162**	**0.022**	**0.000**	**0.174**	**0.022**	**0.000**
McElroy's R^2	0.706			0.576		
Log-likelihood	-1567.853			-1594.308		
Likelihood Ratio				52.913	(P-value = 0.000)	

Table-9d: Parameter Estimates of M4: Log-Quadratic-b Model

	Two-path Model			Single-path Model		
Variable	Coefficient Estimate	Standard Error	P-value for H: β=0	Coefficient Estimate	Standard Error	P-value for H: β=0
	Equation: $\ln(THEATER_j)$			Equation: $\ln(THEATER_j)$		
Intercept	**0.482**	**0.151**	**0.001**	**0.422**	**0.151**	**0.005**
$\ln(\delta+SUPERBOWL_j)$	**0.010**	**0.003**	**0.001**	**0.009**	**0.003**	**0.002**
$\ln(\delta+TVAD_{-1,j})$	**0.322**	**0.036**	**0.000**	**0.316**	**0.037**	**0.000**
$\ln(BUDGET_j)$	**0.070**	**0.022**	**0.001**	**0.081**	**0.022**	**0.000**
$\ln(\delta+LEAD_j)$	-0.031	0.020	0.128	-0.025	0.021	0.233
$\ln(BUZZ_{-1,j})$	0.038	0.021	0.070	**0.041**	**0.021**	**0.053**
$\ln(\delta+PUB_{-1,j})$	0.003	0.002	0.166	0.000	0.002	0.979
GENRE: Action	-0.068	0.054	0.205	-0.067	0.049	0.178
GENRE: Comedy	**-0.147**	**0.050**	**0.003**	**-0.144**	**0.044**	**0.001**
GENRE: Drama	**-0.172**	**0.055**	**0.002**	**-0.165**	**0.050**	**0.001**
MPAA: PG	**-0.137**	**0.065**	**0.037**	-0.120	0.068	0.076
MPAA: PG13	**-0.183**	**0.065**	**0.005**	**-0.167**	**0.066**	**0.012**
MPAA: R	**-0.203**	**0.069**	**0.003**	**-0.185**	**0.071**	**0.009**
WB/New Line	**0.134**	**0.036**	**0.000**	**0.111**	**0.029**	**0.000**
Paramount	**0.087**	**0.042**	**0.041**	**0.069**	**0.034**	**0.044**
Sony	**0.118**	**0.036**	**0.001**	**0.099**	**0.029**	**0.001**
20th Century Fox	**0.147**	**0.043**	**0.001**	**0.117**	**0.032**	**0.000**
Universal	0.092	0.060	0.124	0.062	0.048	0.190
Other Distributors	0.030	0.062	0.627	0.047	0.037	0.203
	Equation: $\ln(BO_j)$			Equation: $\ln(BO_j)$		
Intercept	0.686	0.926	0.459	0.711	0.394	0.071
$THEATER_j$	-0.362	0.804	0.652			
$THEATER_j^2$	**0.240**	**0.110**	**0.029**			
$\ln(\delta+SUPERBOWL_j)$	0.014	0.009	0.100	**0.030**	**0.011**	**0.008**
$\ln(\delta+TVAD_{0,j})$	0.207	0.254	0.416	**0.362**	**0.093**	**0.000**
$\ln(BUDGET_j)$	-0.041	0.074	0.578	**0.160**	**0.055**	**0.004**
$\ln(\delta+LEAD_j)$	-0.008	0.026	0.761	0.016	0.051	0.750
$\ln(BUZZ_{0,j})$	0.066	0.049	0.176	**0.121**	**0.051**	**0.019**
$\ln(\delta+PUB_{0,j})$	**0.017**	**0.004**	**0.000**	**0.021**	**0.005**	**0.000**
GENRE: Action	**0.322**	**0.150**	**0.032**	0.165	0.104	0.112
GENRE: Comedy	0.258	0.168	0.124	-0.005	0.071	0.943
GENRE: Drama	0.267	0.182	0.144	-0.080	0.093	0.391
MPAA: PG	-0.207	0.139	0.138	-0.193	0.167	0.248
MPAA: PG13	-0.150	0.145	0.300	-0.187	0.149	0.211
MPAA: R	-0.143	0.153	0.350	-0.230	0.156	0.142
SEASON: Jan-Apr	0.036	0.068	0.595	-0.013	0.082	0.878
SEASON: May-Aug	**0.289**	**0.073**	**0.000**	**0.348**	**0.081**	**0.000**
SEASON: Nov-Dec	**0.225**	**0.089**	**0.011**	**0.289**	**0.094**	**0.002**
$HOLIDAY_j$	**0.171**	**0.069**	**0.013**	**0.181**	**0.075**	**0.016**
$\ln(CRITICS_j)$	**0.815**	**0.102**	**0.000**	**0.927**	**0.103**	**0.000**
McElroy's R^2	0.712			0.519		
Log-likelihood	-1576.426			-1617.683		
Likelihood Ratio				82.515	(P-value = 0.000)	

Table-10: Comparison of the effectiveness of Super Bowl and Other Launch TV advertising

	Effects on *$THEATER_j$* **H3a: $\beta_{1,SB}=\beta_{1,AD}$**		**Effects on *BO_j*** **H3b: $\beta_{2,SB}=\beta_{2,AD}$**	
	t-statistic	P-value	t-statistic	P-value
M1: Log-linear	0.459	0.647	2.137	0.033
M2: Log-Log	-8.313	0.000	0.774	0.439
M3: Log-Quadratic-a	-7.222	0.000	-1.386	0.167
M4: Log-Quadratic-b	-8.768	0.000	-0.772	0.441

Table-11: Elasticity Measures on the basis of M3, the Log-quadratic-a Model

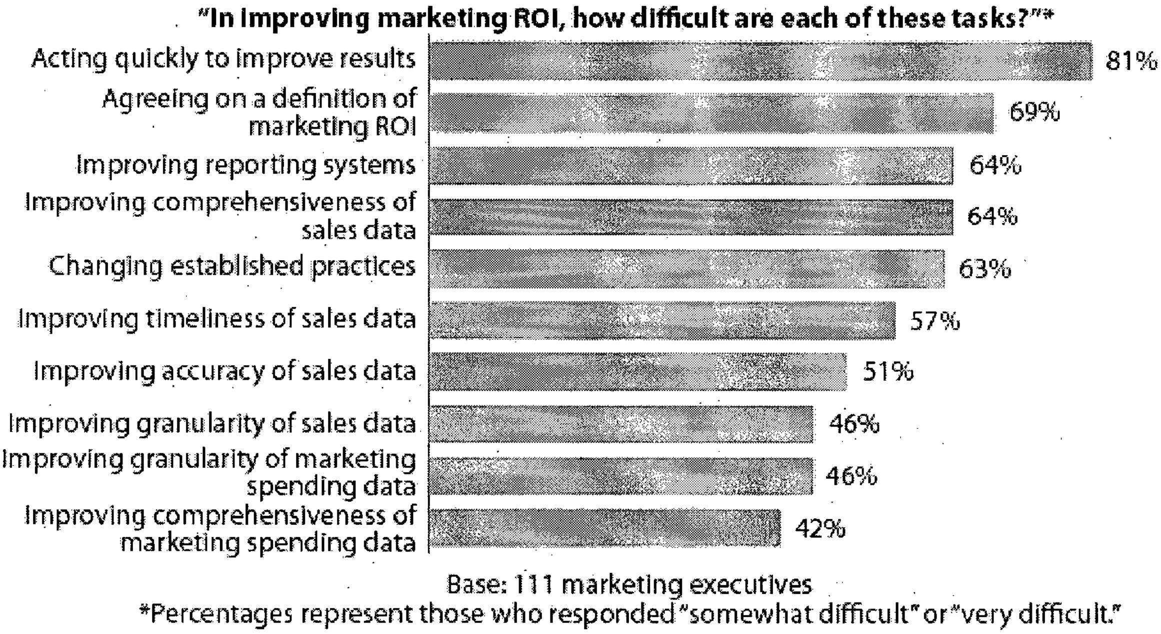
		Two Causal Paths from Super Bowl TV advertising to Opening Week Box Office Revenues											
		Indirect Effect						Direct Effect			Total Effect		
		$e_{SB\text{-}THR}$			$e_{THR\text{-}BO}$						$e_{SB\text{-}BO}$		
THEATER		Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value
Mean:	2.336	0.006	0.003	0.019	1.309	0.695	0.060	0.017	0.008	0.034	0.026	0.010	0.011
1st quartile	1.892				0.696	0.713	0.330				0.022	0.009	0.016
Median	2.491				1.563	0.675	0.021				0.027	0.010	0.010
3rd quartile	2.783				2.099	0.626	0.001				0.031	0.011	0.008

		Two Causal Paths from Other Launch TV advertising to Opening Week Box Office Revenues											
		Indirect Effect						Direct Effect			Total Effect		
		$e_{AD\text{-}THR}$			$e_{THR\text{-}BO}$						$e_{AD\text{-}BO}$		
THEATER		Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value
Mean:	2.336	0.292	0.040	0.000	1.309	0.695	0.060	0.231	0.159	0.148	0.613	0.107	0.000
1st quartile	1.892				0.696	0.713	0.330				0.434	0.088	0.000
Median	2.491				1.563	0.675	0.021				0.687	0.115	0.000
3rd quartile	2.783				2.099	0.626	0.001				0.843	0.136	0.000

Table-A1: Regression Results for *IMDb_ALEXA*$_d$

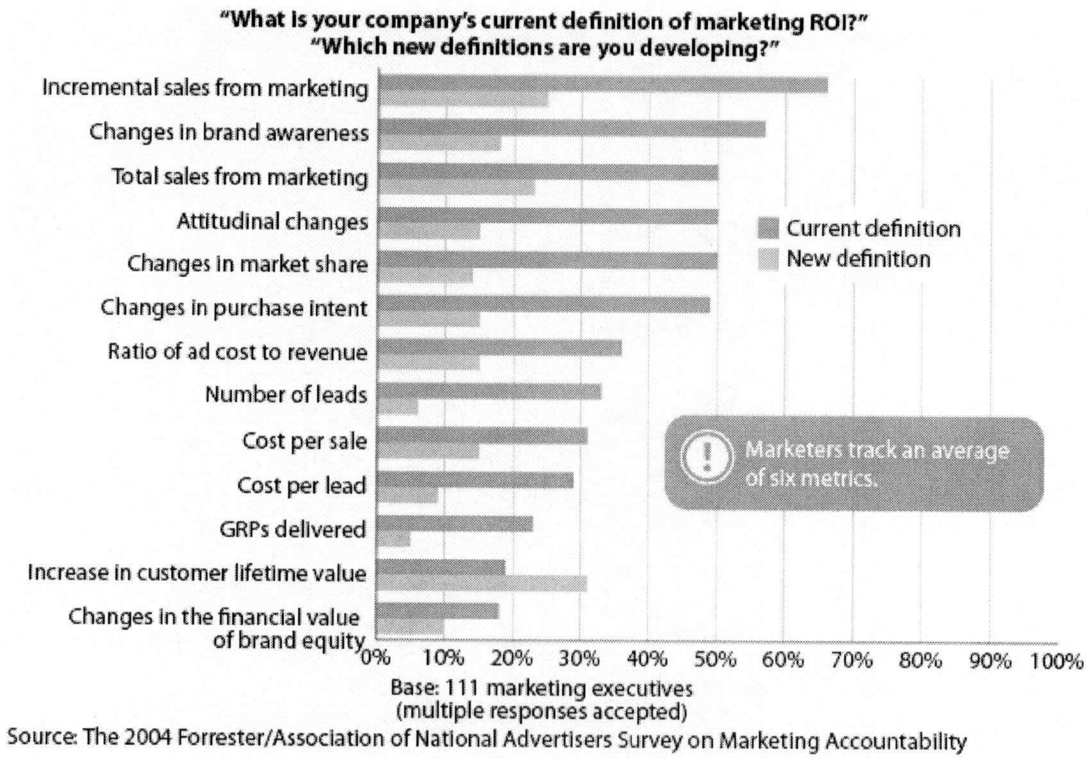
Variables	Parameter Estimates	Standard Errors	P-values
	ln($IMDb\_ALEXA_d$)		
Intercept	12.67	0.06	0.00
$Trend_w$	0.01	0.00	0.00
FEB	-0.03	0.05	0.59
MAR	-0.10	0.05	0.05
APR	-0.09	0.05	0.06
MAY	-0.08	0.05	0.08
JUN	-0.10	0.05	0.03
JUL	-0.06	0.05	0.25
AUG	-0.09	0.05	0.04
SEP	-0.04	0.05	0.46
OCT	-0.12	0.05	0.01
NOV	-0.14	0.06	0.03
DEC	-0.12	0.04	0.01
NEW YEAR	0.15	0.05	0.01
MARTIN LUTHER KING DAY	0.05	0.07	0.47
PRESIDENTS DAY	-0.10	0.09	0.25
MEMORIAL DAY	-0.02	0.06	0.79
INDEPENDENCE DAY	0.02	0.08	0.79
LABOR DAY	-0.03	0.08	0.69
COLUMBIA DAY	-0.08	0.07	0.25
VETERANS DAY	-0.05	0.09	0.56
THANKSGIVING DAY	-0.04	0.08	0.65
XMAS	0.11	0.06	0.07
N	180		
R^2	0.94		

Figure-1: Survey Results for Difficulties in Marketing Metrics



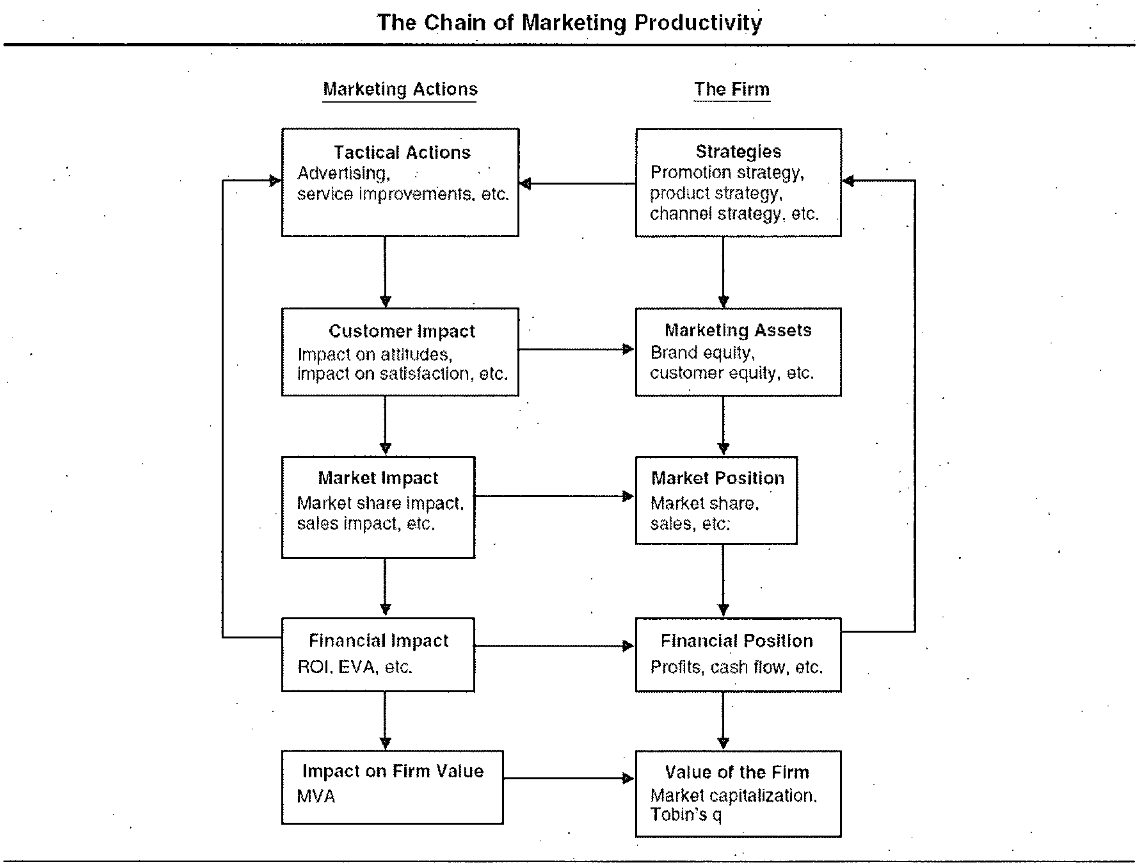
(Reproduced from Nail 2005)

Figure-2: Survey Results for Definition of Marketing Metrics



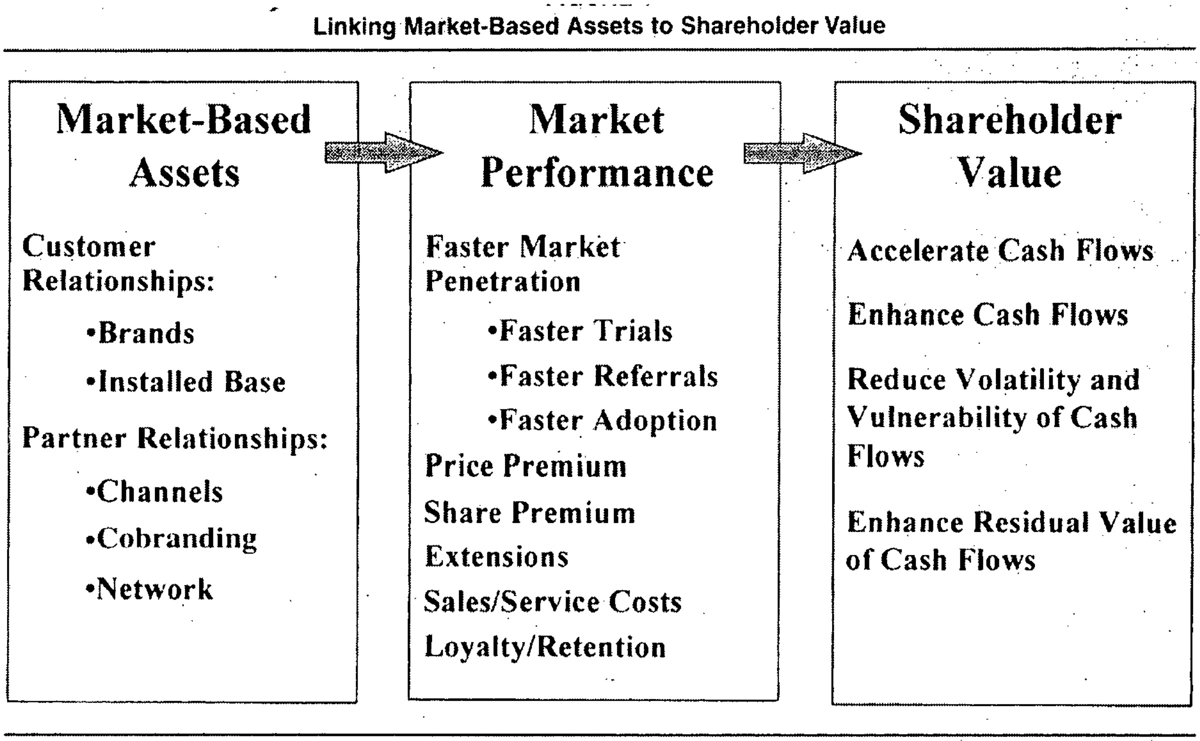
(Reproduced from Nail 2005)

Figure-3: A Research Framework proposed by Rust et al. (2004)



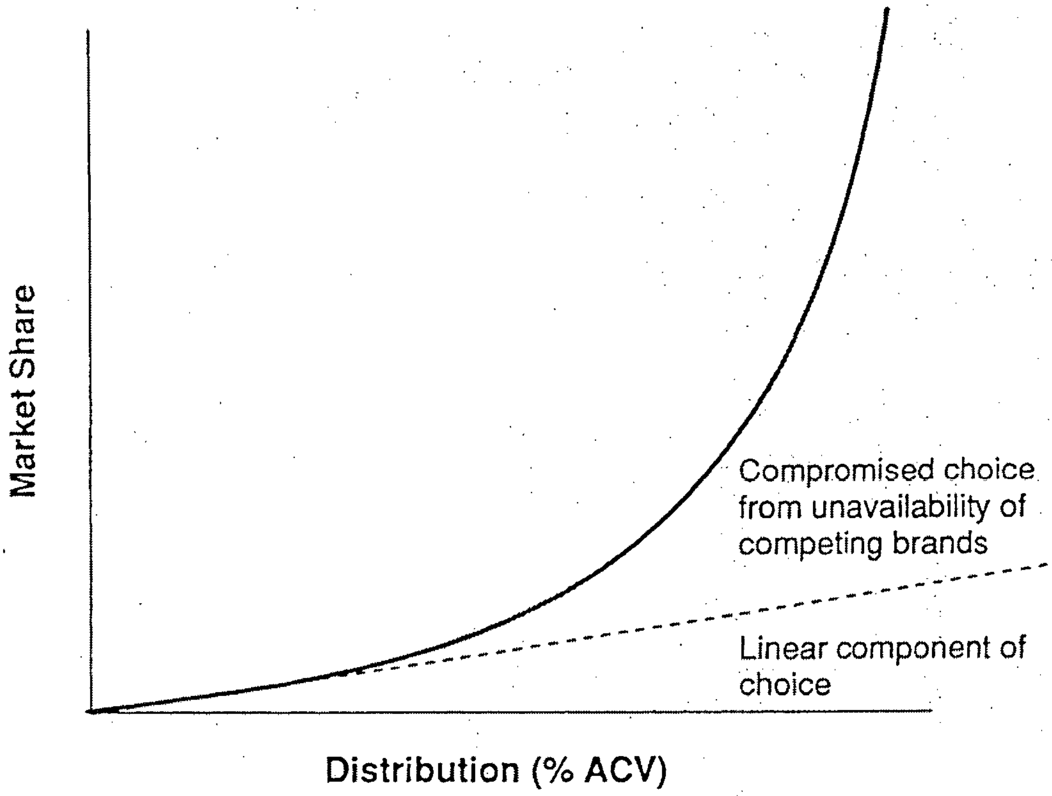
(Reproduced from Rust et al. 2004)

Figure-4: A Marketing-Shareholder Value Framework proposed by Srivastava et al (1998)



(Reproduced from Srivastava et al. 1998)

Figure-5: Cross-sectional relationships between brand share and retail distribution in packaged goods show a convex pattern



%ACV is the percentage of total outlet sales in "all commodity groups" made by stores that stock the product category

(Reproduced from Reibstein and Farris 1995)

Figure-6a: A two-path model of Super Bowl and other launch TV advertising

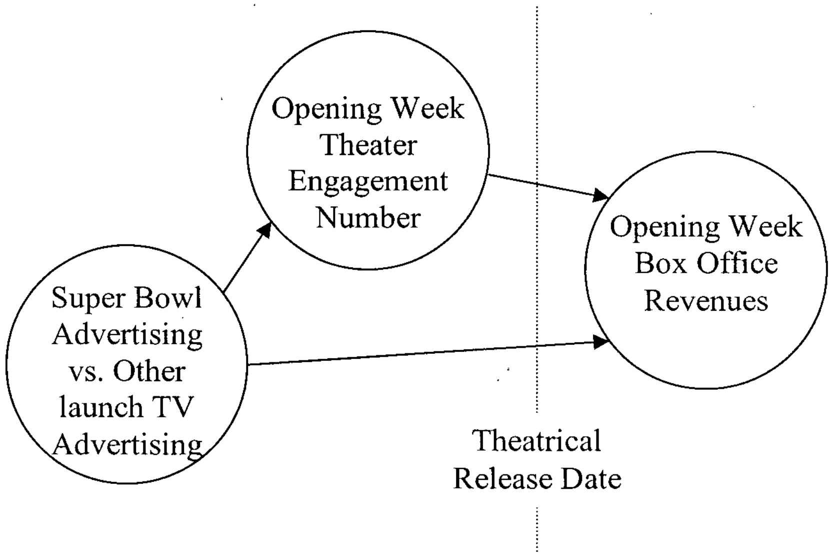


Figure-6b: A single-path model of Super Bowl and other launch TV advertising

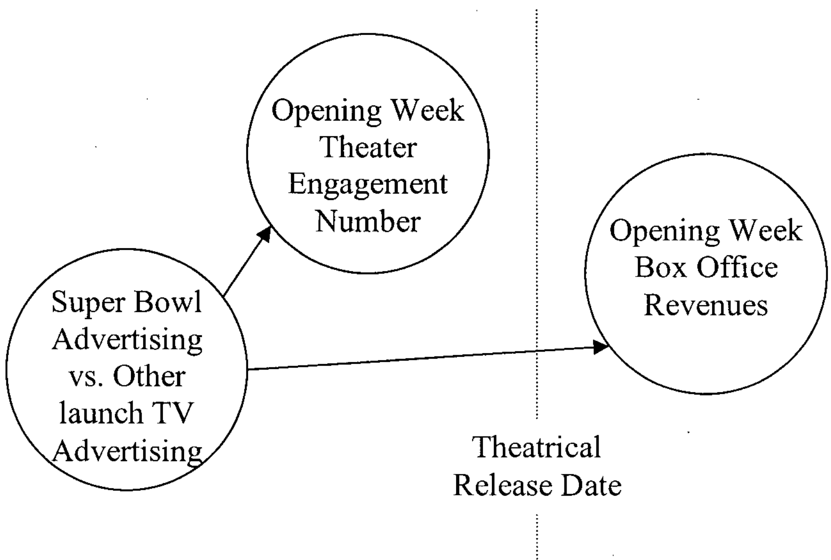


Figure-7: Distribution of Theater Numbers in the Release Week by Individual Movies

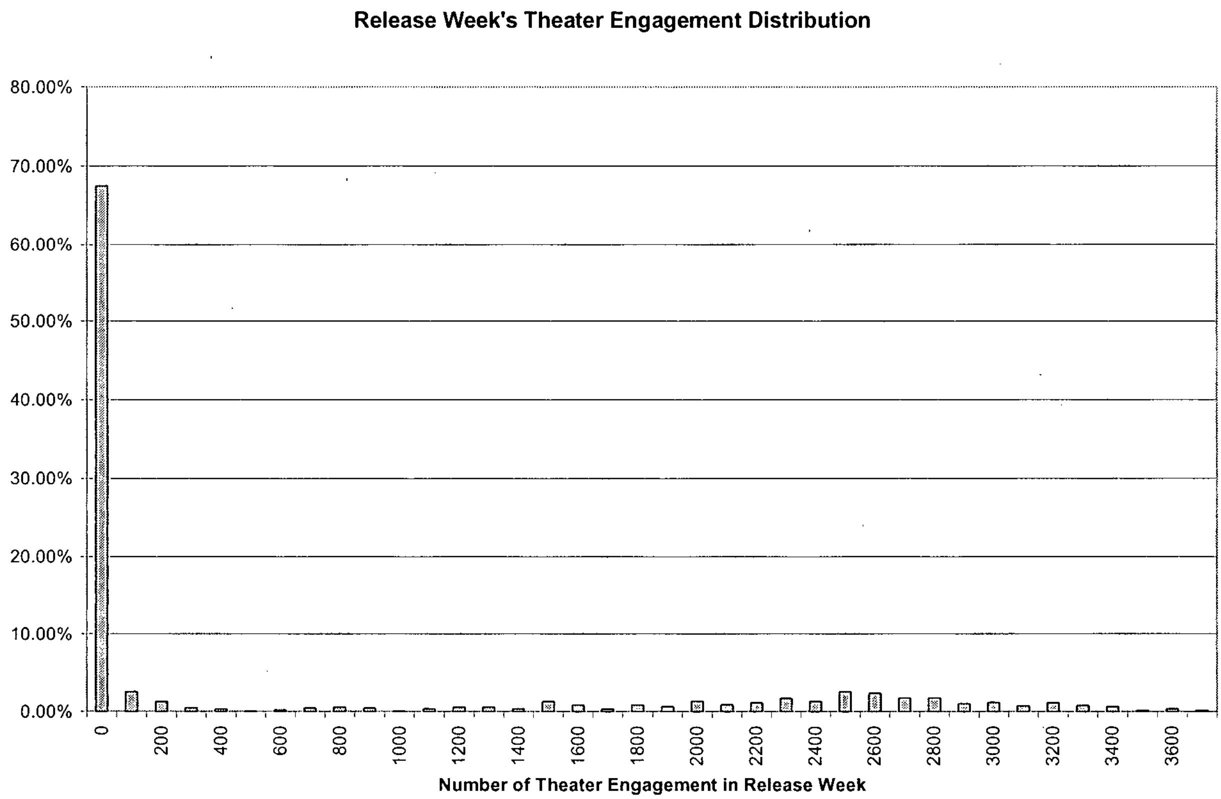


Figure-8: An example to show the definitions of six Duration-based Variables

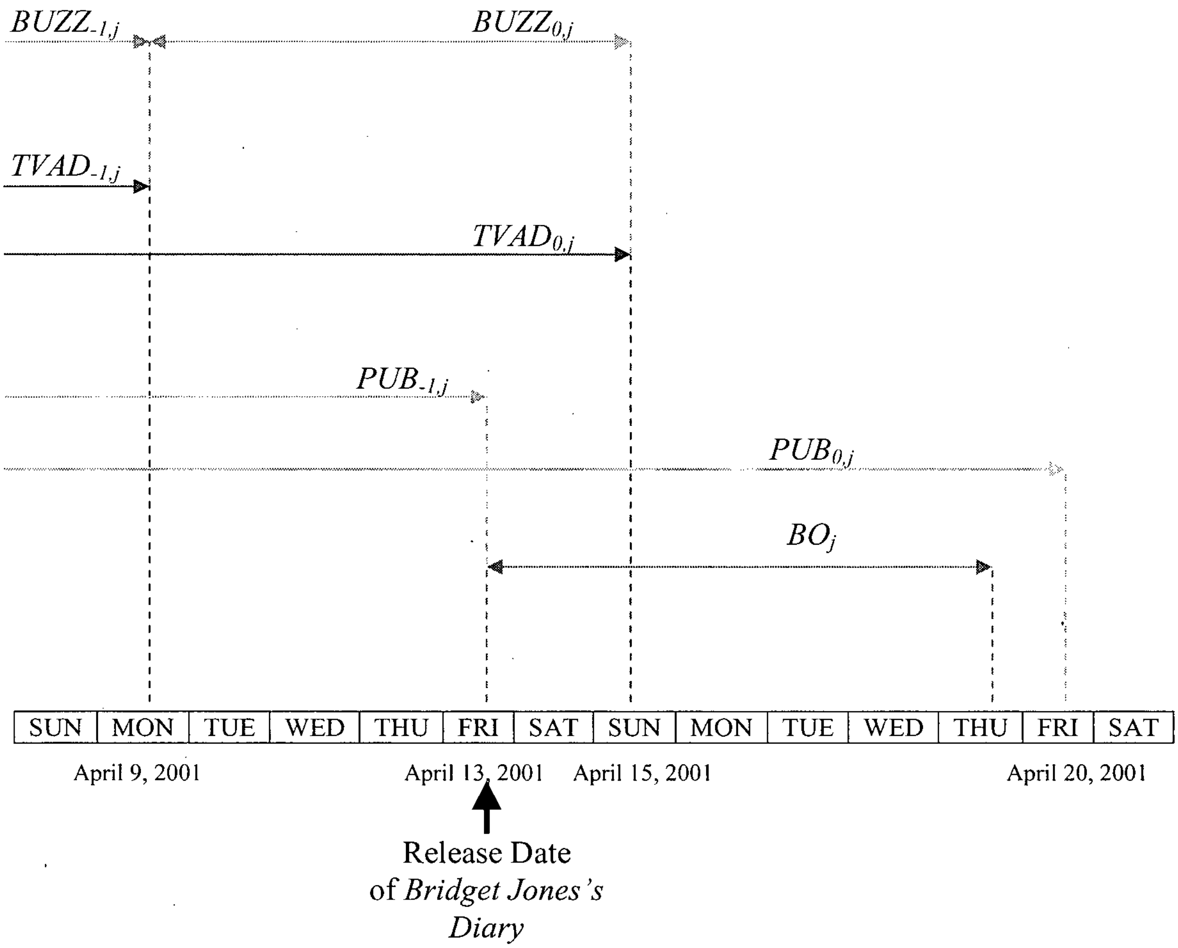


Figure-9a: Box Plot of *BO_j*
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

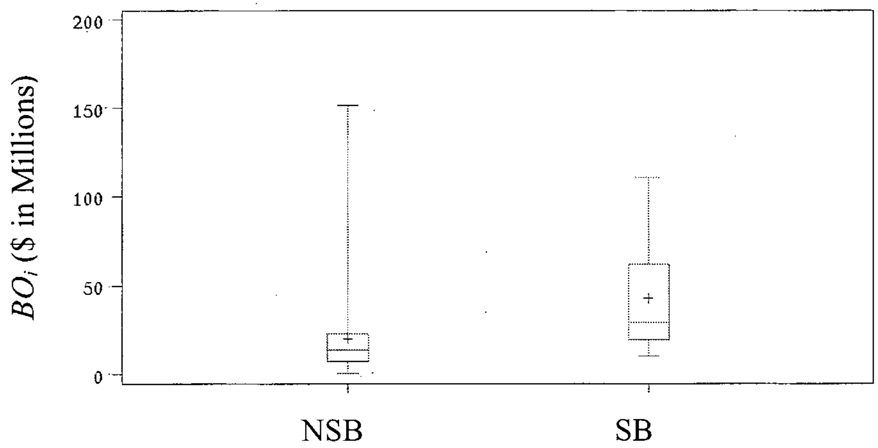


Figure-9b: Box Plot of *$THEATER_j$*
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

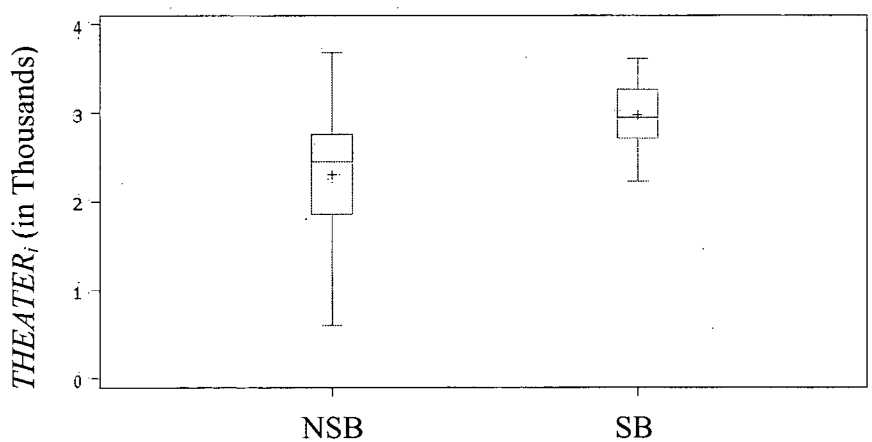


Figure-9c: Box Plot of *$TVAD_{-1,j}$*
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

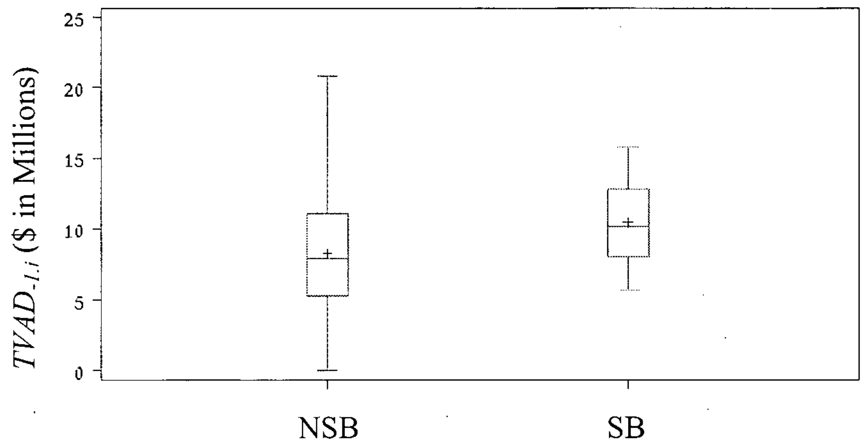


Figure-9d: Box Plot of *$TVAD_{0,j}$*
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

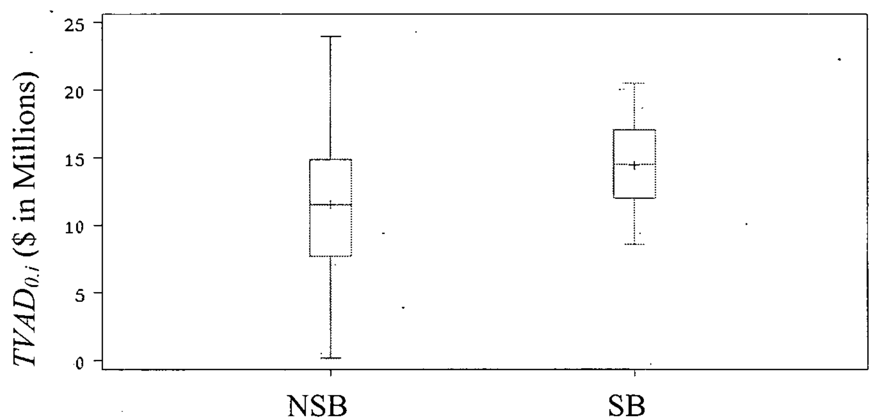


Figure-9e: Box Plot of $LEAD_j$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

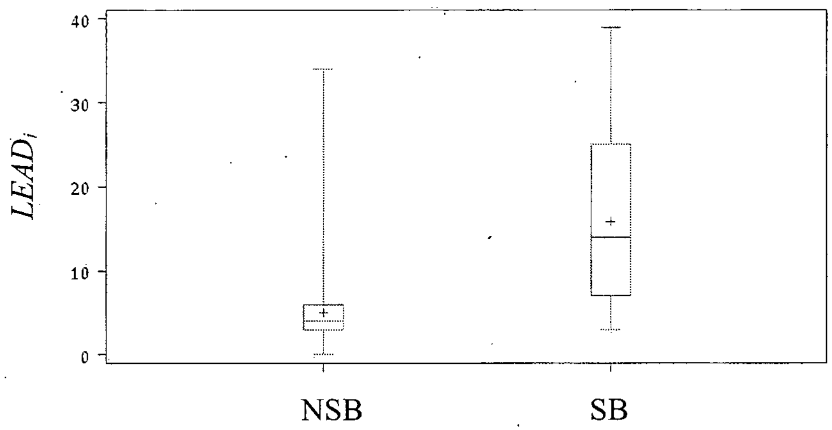


Figure-9f: Box Plot of $BUDGET_j$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

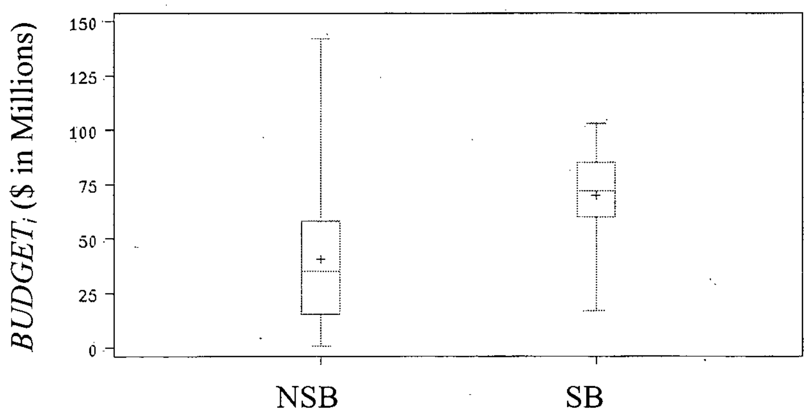


Figure-9g: Box Plot of $BUZZ_{-1,j}$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

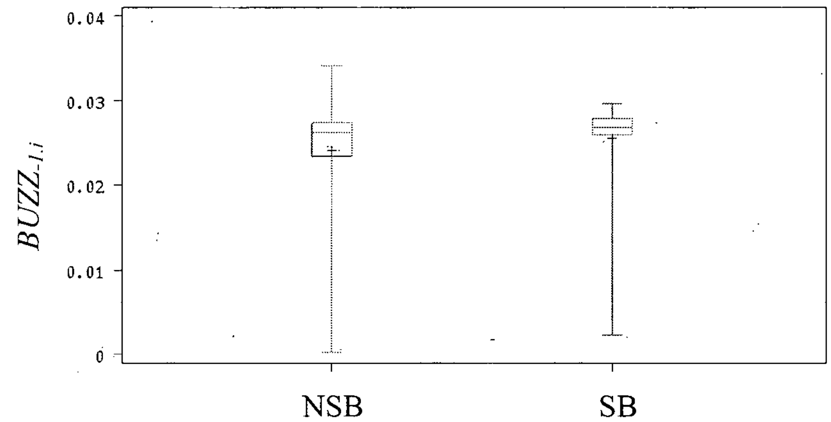


Figure-9h: Box Plot of $BUZZ_{0,j}$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

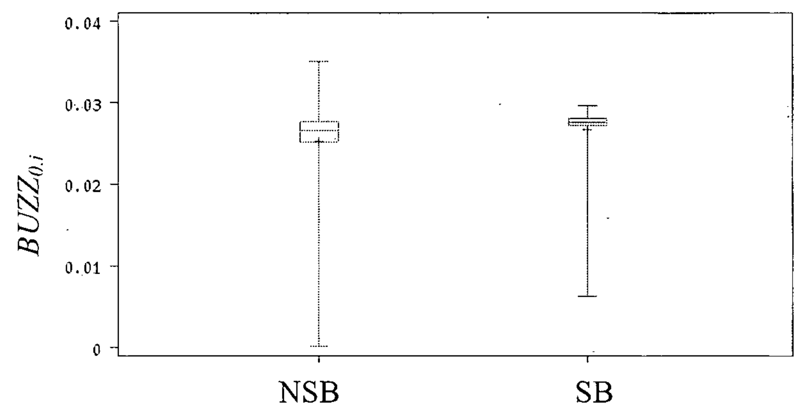


Figure-9i: Box Plot of $PUB_{-1,j}$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

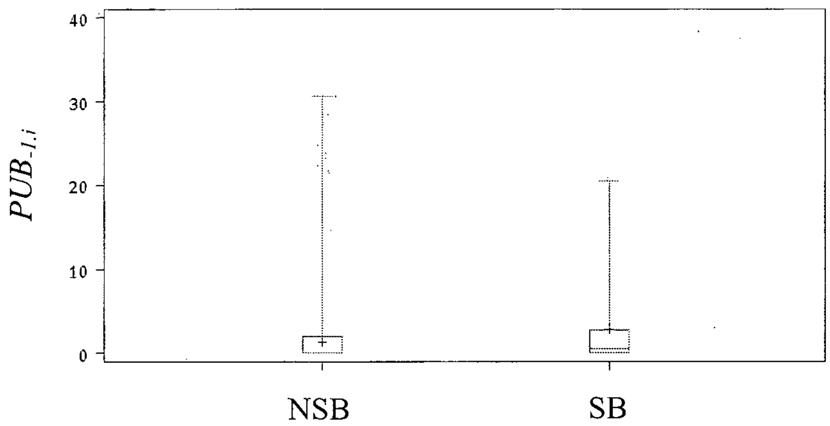


Figure-9k: Box Plot of $CRITICS_j$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

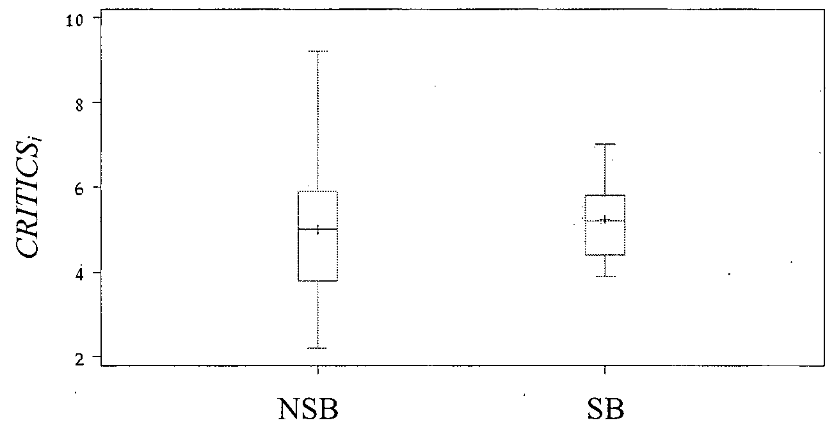


Figure-9j: Box Plot of $PUB_{0,j}$
Non-Super Bowl advertised Movies (NSB)
vs. Super Bowl advertised Movies (SB)

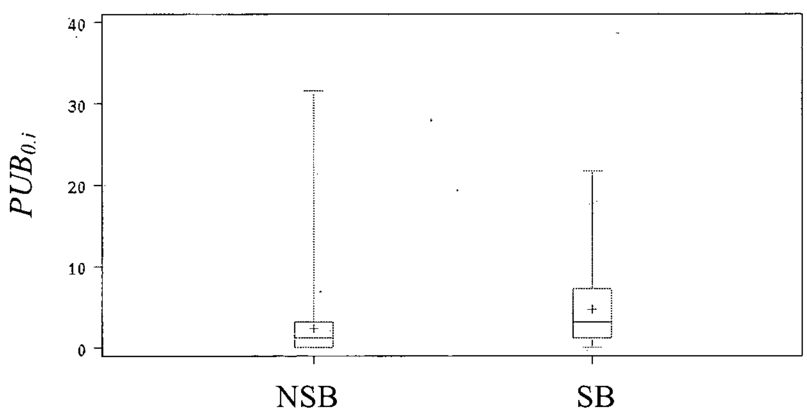


Figure-10a: Simulated *THEATER* by Individual Scenarios

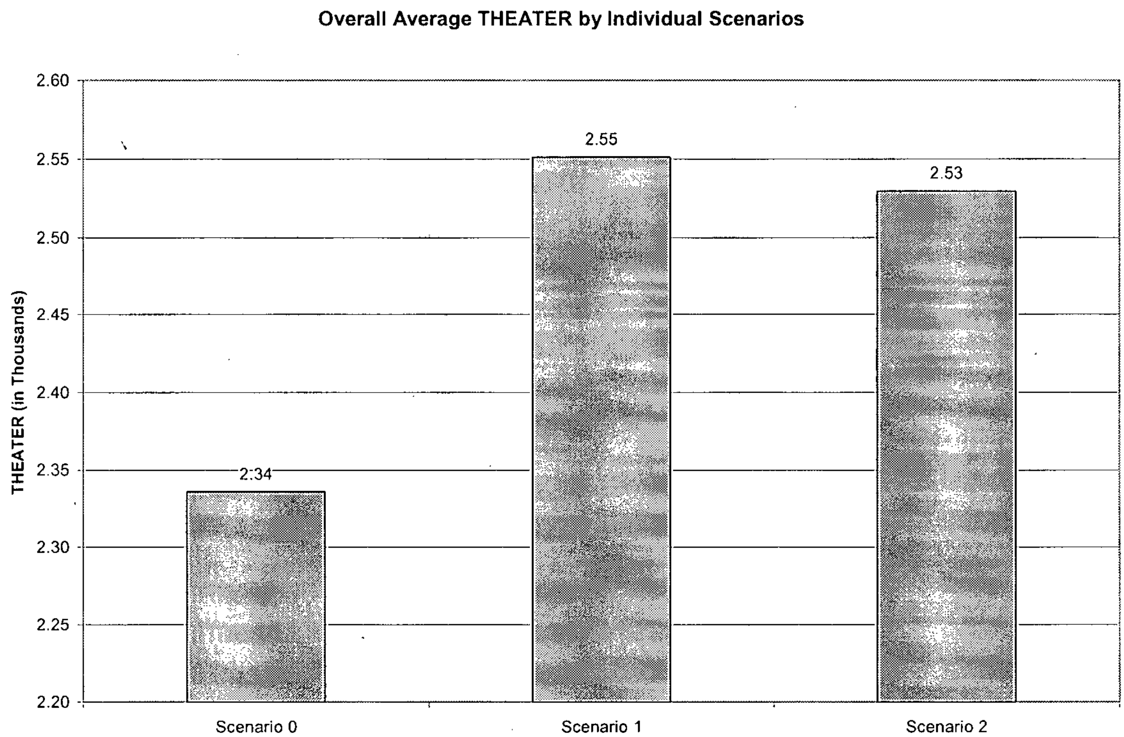


Figure-10b: Simulated *BO* by Individual Scenarios

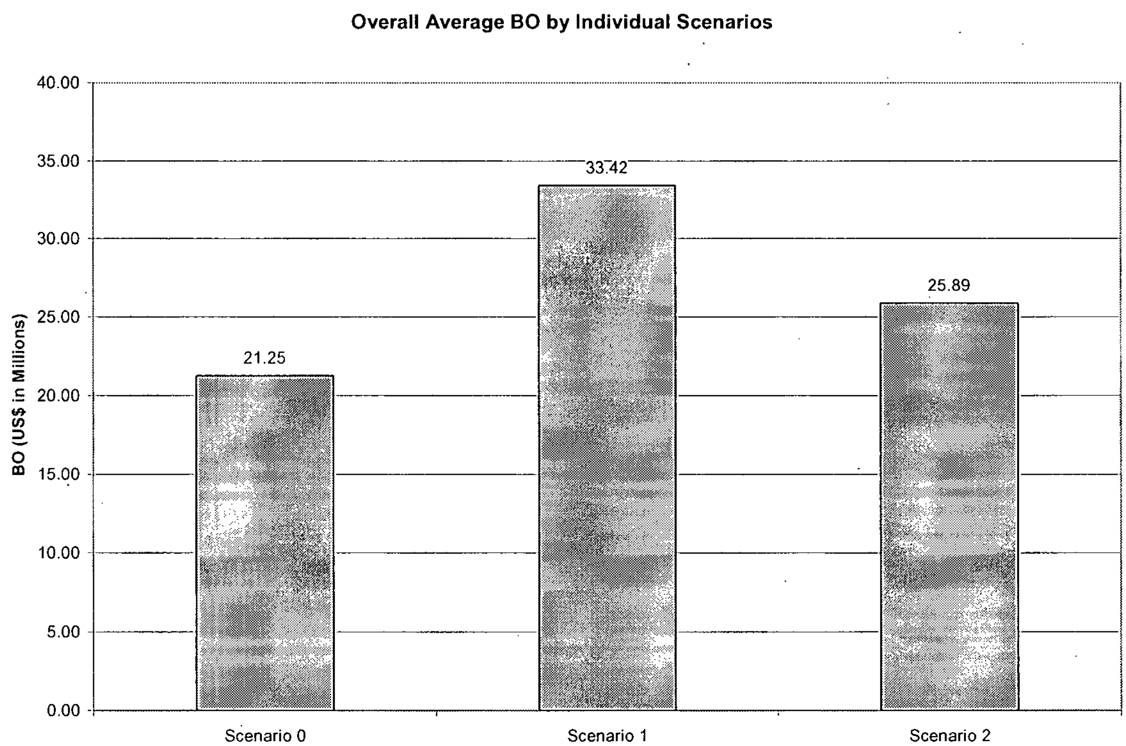


Figure-10c: Simulated *THEATER* by Individual Scenarios: SB vs. NSB

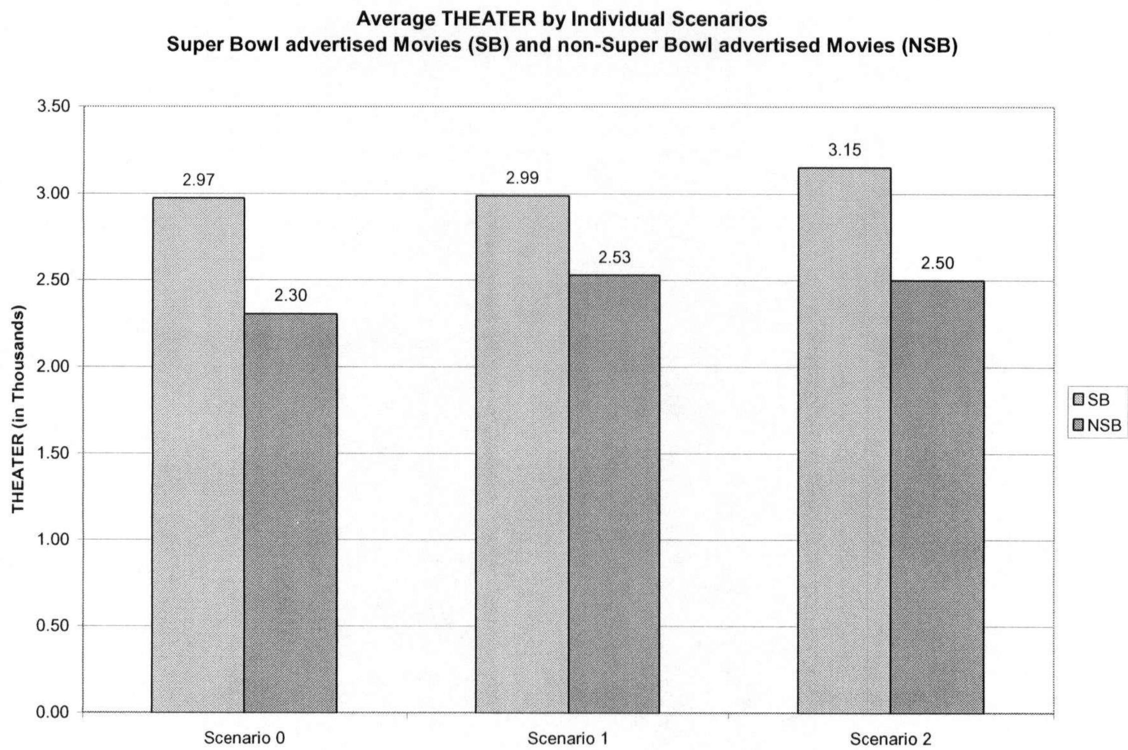


Figure-10d: Simulated *BO* by Individual Scenarios: SB vs. NSB

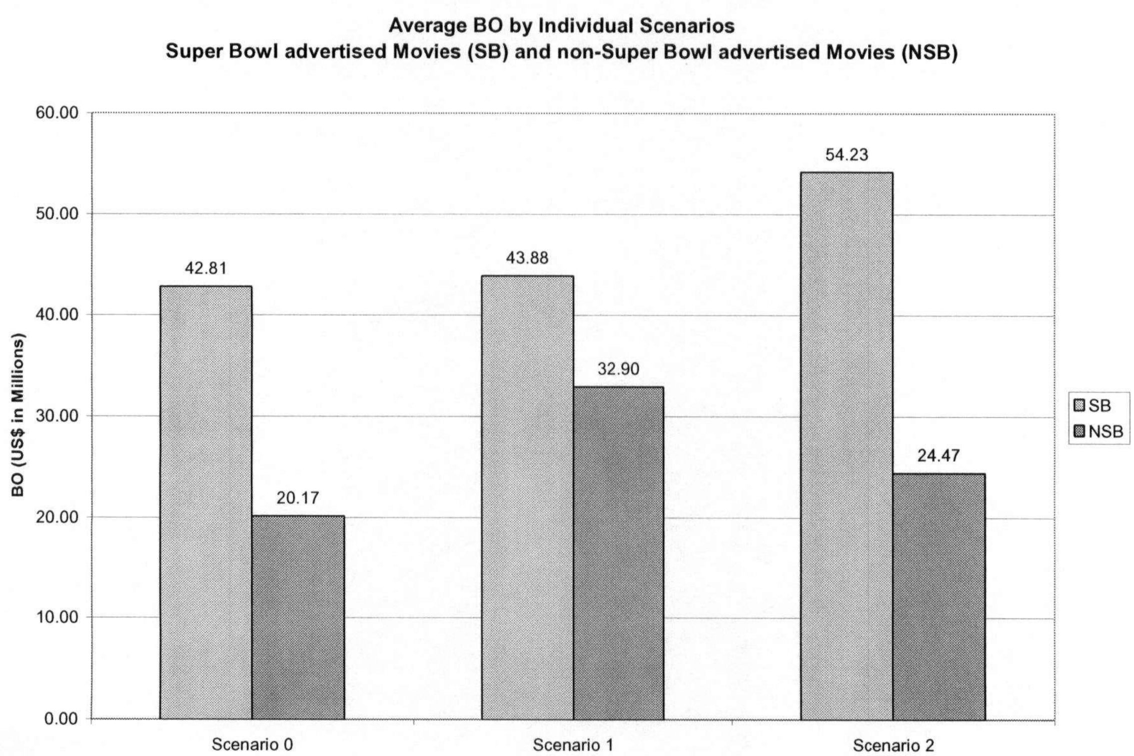


Figure-11a: *THEATER* Response Function w.r.t. *SUPERBOWL*

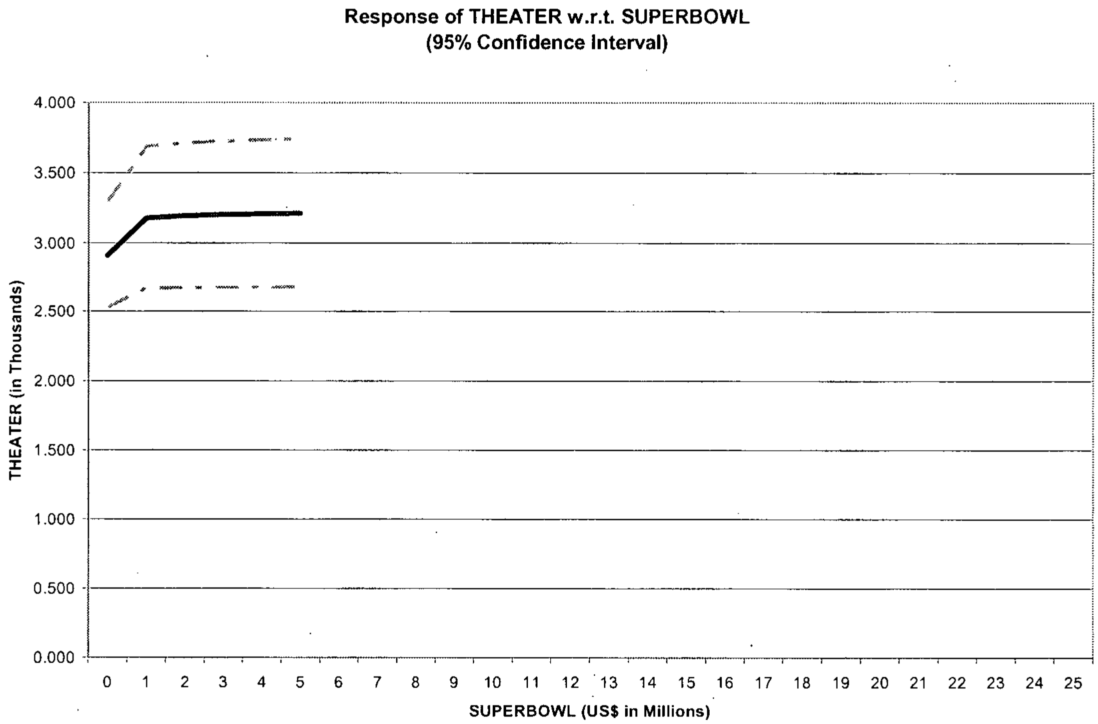


Figure-11b: *THEATER* Response Function w.r.t. *TVAD*$_{-1}$

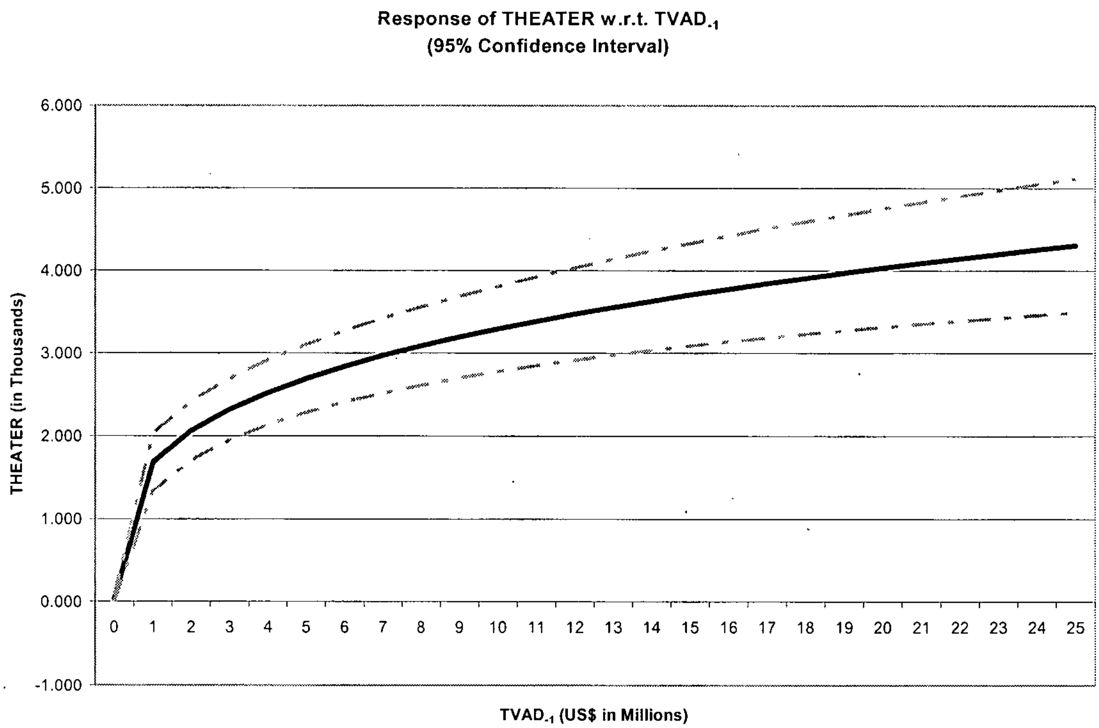


Figure-11c: *BO* Response Function w.r.t. *SUPERBOWL*

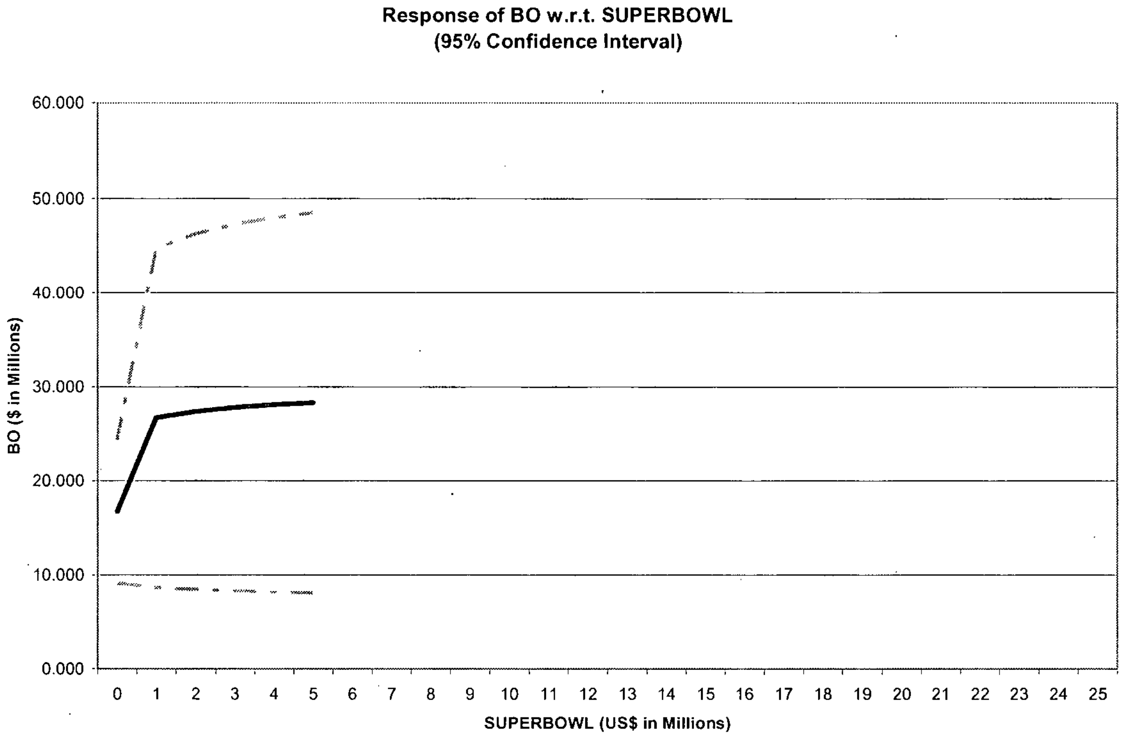


Figure-11d: *BO* Response Function w.r.t. *TVAD$_{-1}$*

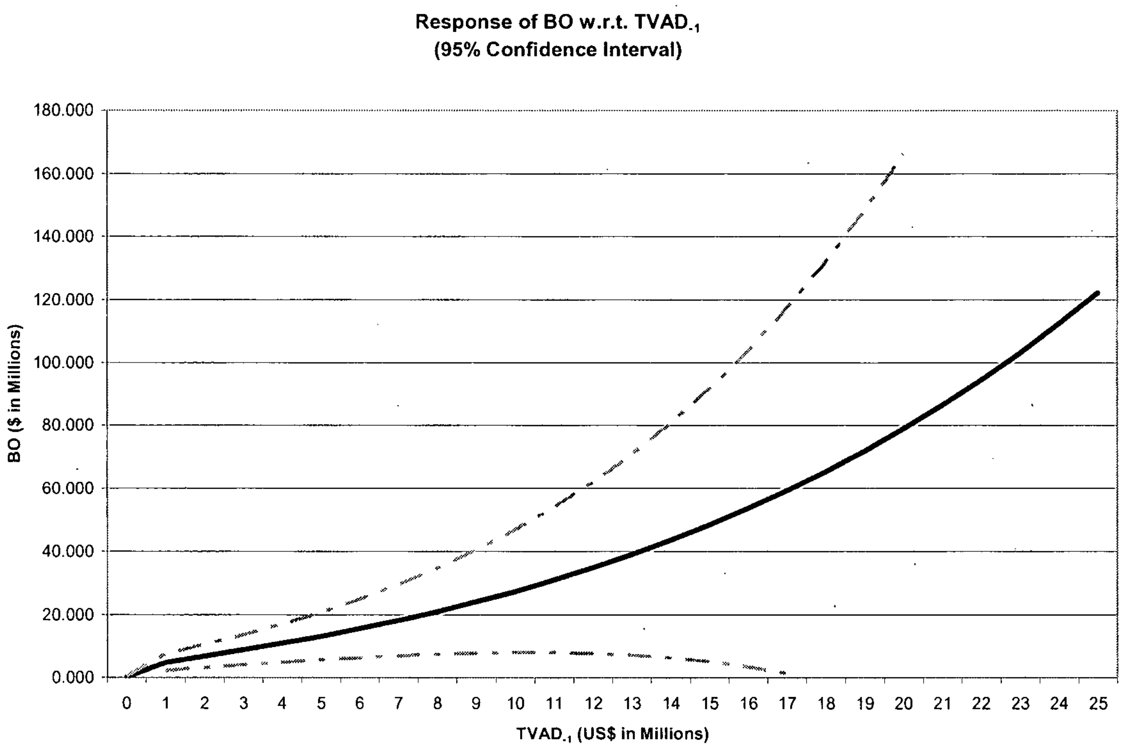


Figure-11e: *BO* Response Function w.r.t. *THEATER*

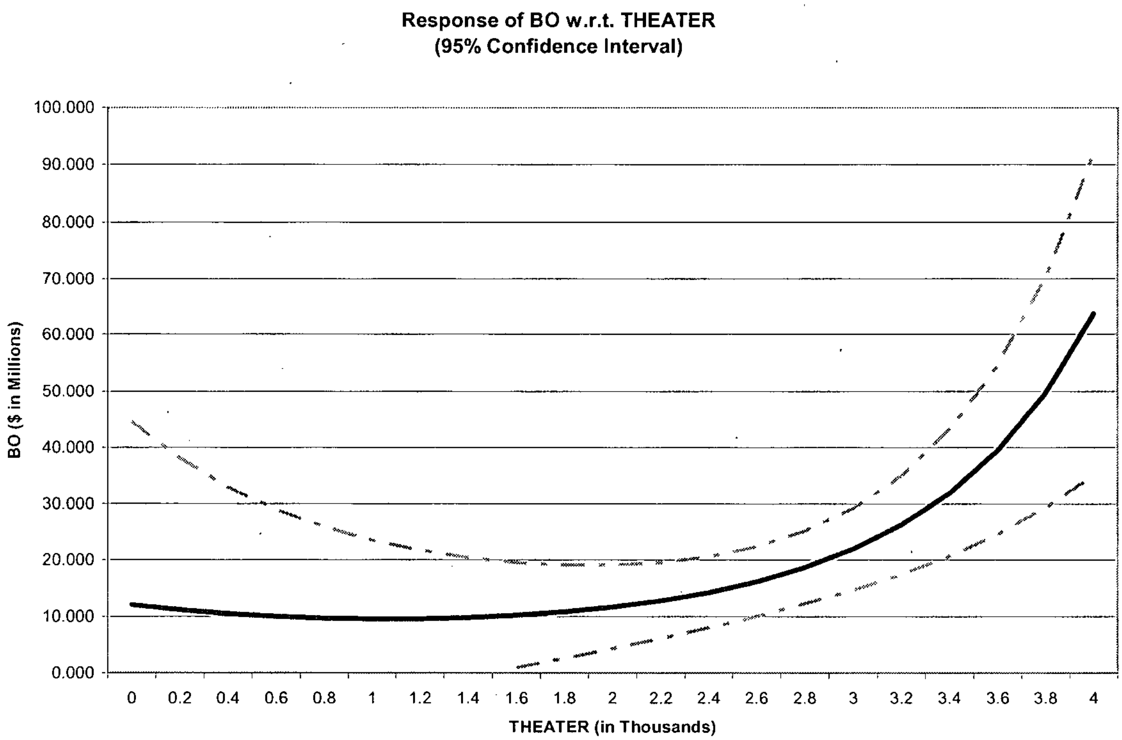
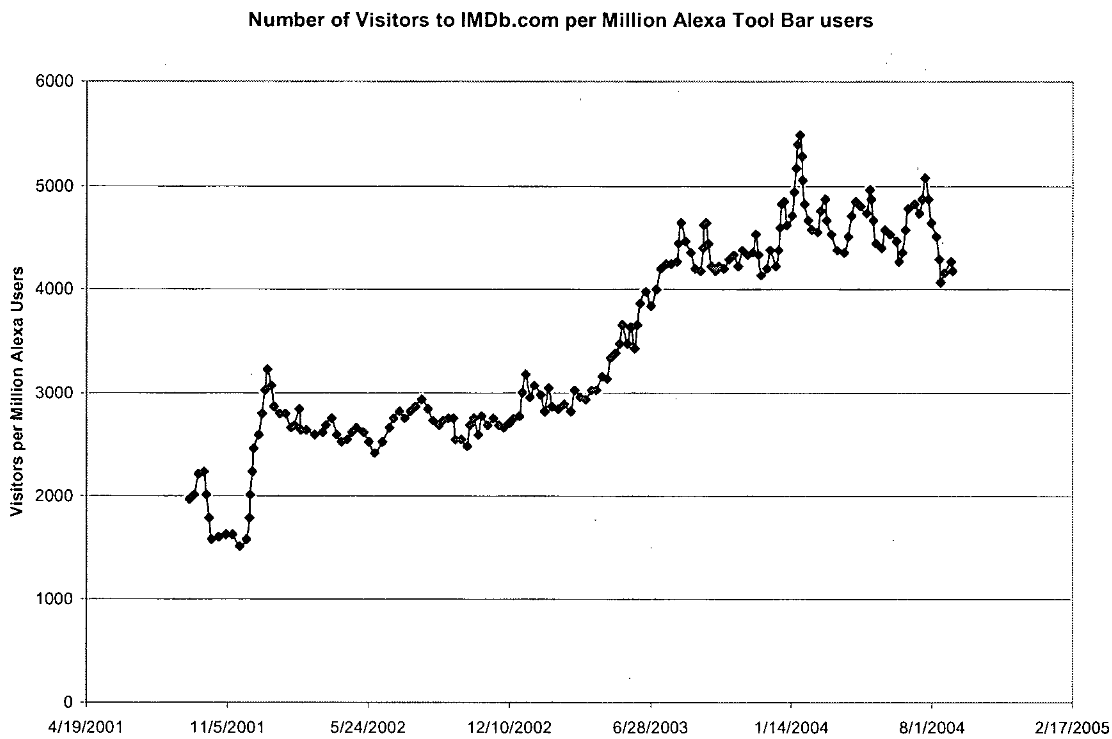


Figure-A1: Number of Visitors to *IMDb.com* per Million *Alexa* Tool Bar users



Chapter 4: Good Movie or Nothing Better to Do?

Time of Day Demand Models for Multiplex Movie Theaters

1. Introduction

Many service providers, such as movie theaters and airlines, serve a cohort of customers according to pre-announced time schedules, rather than serving individual customers as they arrive or order. For these pre-announced time schedule service providers, choosing the optimal service time schedule is crucial to profit maximization. On the one hand, the time schedule is an operation plan, which aligns different cost centers, like human resources and capacity management, to achieve the most cost-efficient operation. On the other hand, customers decide if they want to purchase services from a service provider on the basis of its pre-announced time schedule. If a customer cannot find any services scheduled by a service provider that match her preferred start/end time, she may switch to a competing service provider or pursue an outside alternative. In other words, like price and service quality, the start/end time of a service is potentially an important choice attribute in determining consumer demand. Focusing on multiplex movie theaters, this essay develops demand models, which disentangle consumer preferences for different start times from aggregate historical sales data[1]. In particular, the demand models address two recurring issues in multiplex movie theaters and similar service providers, namely the confounding of product quality and time preferences, and the difficulty of distinguishing between cannibalization and market expansion. The demand models are intended to be used by multiplex movie managers and other service providers, which need to pre-announce their service schedules, to optimize their service schedules.

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[1] An alternative approach to understanding customer time preference is to conduct a market survey, asking the customers explicitly their preferred start/end times for various service offerings. However, this approach is usually very costly and subject to various sampling biases.

Let us take a closer look at the first issue. We, as researchers and analysts, cannot observe moviegoers' perceptions concerning the quality of each movie. If a theater manager, however, had some idea of moviegoers' perceptions of quality, and had a tendency to schedule high-perceived-quality movies in a particular time slot, say 9 pm, it is unclear whether high attendance at 9 pm in the historical sales data was due to moviegoers' underlying time preferences or higher movie quality perceptions. Moviegoers' time preference and their preference for movies are essentially confounded. To put it lightly, we cannot distinguish whether moviegoers choose to watch a movie because it is a good film, or because they have nothing better to do at that time. While this problem is particularly apparent in multiplex movie theaters, other service providers who schedule differentiated services at different times of day may encounter the same problem. To address this issue, we characterize the choice set of potential moviegoers in a particular hour as one consisting of the movie showings starting in the hour and an option to not watch any movie. The not-watching option includes all other alternatives such as going to movies starting at another time, going to another multiplex movie theater, going to museums, spending time with friends in coffee shops, working in the office, studying, and so on. Referring to these other options (outside the choice of watching a movie in a specific hour at the focal movie theater) the "outside option", we assume that the attractiveness of the outside option varies over time of day, day of week and time of year, while the appeal of watching a movie title at a theater decays over weeks but stays constant within a week. By capturing the time variations of the outside option, relative to the systematic decay of unobserved movie quality in a utility model, we disentangle moviegoers' underlying time preference and their preference for movie titles in the aggregated sales data. Our approach is similar to Einav's (2003), through which he identifies the weekly seasonality over a year at the total U.S. market level. However, the present research differs from his work in three aspects. First, we go beyond weekly seasonality to examine all three layers of seasonality, namely time of day, day of week, and day of year. And we do it at a more micro level, that of multiplex theaters, as opposed to the whole U.S. market. Second, we improve on his specification by allowing a more flexible weekly decay of the unobserved movie quality. Finally, we extend the model to address the second issue common to pre-announced time schedule service providers: the difficulty of distinguishing between cannibalization and market expansion.

Let us examine the second issue in more detail. This issue is a mainstay concern in the discrete choice literature, but is especially apparent in our context. When modeling consumer demand for different services within an hour as discrete choice occasions, we must assume the manner in which the unobserved utility components in individual alternatives are correlated. Two commonly used models, which assume different structures of such correlation, are probit and nested logit models.[2] While these models have been shown to be satisfactory solutions in situations where the choice sets are relatively constant across choice occasions, it is not clear if they are as effective when there is non-trivial variation in the choice set. Specifically, in the context of demands for service scheduling, the choice set in general and the number of choice alternatives in particular varies from one choice occasion to another. For example, there were two movies, say *Batman Begins* and *The Interpreter*, starting within the hour beginning at 7pm on a specific Monday, but *Star Wars Episode III* was added to this choice set within the hour of 7pm the next Tuesday. Beside accounting for the different time preferences between Monday and Tuesday, it is necessary for our demand model to identify two effects triggered by the addition of *Star Wars Episode III*: 1) overall demand expansion effect (the additional title is attracting new moviegoers, who would not go to the theater otherwise), and 2) cannibalization effect (the additional title is prompting "decided" moviegoers to switch from the other titles).

[2] Refer to Train 2001 for an overview.

Due to the well-known property of Independence of Irrelevant Alternatives (IIA), the standard logit model is unable to distinguish these two effects. We therefore need discrete choice models, which relax the IIA property. Explicitly modeling the correlation of individual choice alternatives, the multinomial probit model usually faces increasing challenges in estimation as the number of unique choice alternatives increases. As the aggregated sales data of a multiplex movie theater typically contain a large number of unique movie titles, the probit model is almost infeasible to implement, or at least incurs a high cost of implementation. Another approach to overcoming IIA is the mixed logit model. However, as there is no apparent demographic or other cross-sectional variation of moviegoers across our units of observation, which are different time slots for a focal movie theater, the random coefficient specification in the mixed logit model is not very useful to our context. Therefore, this essay focuses on the nested logit model and a model suggested by Ackerberg and Rysman (2002). Both models will be applied to our context of multiplex movie theaters and their relative merits in identifying the cannibalization and market expansion effects will be discussed.

In summary, this essay develops a model addressing two issues, namely the confounding of underlying seasonality and unobserved product quality, and the difficulty of distinguishing between cannibalization and market expansion effects. These two issues are recurring but relatively under-researched issues in marketing practice. The multiplex movie theater context provides a unique opportunity and data set for addressing these problems in an integrated manner. To the best of our knowledge, this is the first attempt to address the two problems together. This research advances our methodology for helping companies frequently facing both problems.

The next section reviews the literature streams related to this essay. Section 3 discusses three models. First, we present the base model to illustrate how the underlying time preferences of moviegoers are disentangled from the unobserved movie qualities. To identify the cannibalization and market expansion/subtraction effects of varying choice sets, we then extend the base model in two directions, using the nested logit approach and Ackerberg and Rysman's approach. The demand models are estimated with two data sets from a multiplex movie theater in the Netherlands. Section 4 describes the data sets and section 5 discusses the estimation results. Section 6 concludes the essay with a discussion of the limitations of our study and future research directions.

2. Related Literature

This essay is related to two literature streams. First, our demand model adds to the broad literature of market response models for managers. Second, we advance the literature related to discrete choice models with market-level data.

2.1 Market Response Models for Managers

Similar to their counterparts for the use of policy makers, market response models for managers attempt to represent reality using parsimonious mathematical models. These models may stand alone as predictive or diagnostic models (refer to Hanssens, Parsons and Schultz 2003 for a comprehensive review) or be incorporated into the decision optimization procedure in marketing management support systems (MMSS) (see Wierenga and Bruggen 2000 for a review of MMSS). Our demand model extends the literature by focusing on an under-researched marketing decision variable, namely "what to offer in a choice occasion".

As reviewed by Hanssens, Parsons and Schultz (2003), extant market response models are primarily concerned with advertising, pricing or other decisions in which the decision alternatives are at least ordinal in nature. For example, to distinguish between the carryover effect of advertising and the effect of purchase feedback, Givon and Horsky (1990) built a response model relating sales levels in a current period to current and previous advertising levels and the last period's sales level. Regarding the focal decision in their study - advertising level - we can readily rank one decision alternative over the other (e.g., $25,000 is higher than $10,000). In contrast, our demand model concerns the type of decisions in which decision alternatives cannot be readily ordered. Specifically, our focal decision is different pre-announced service schedules. In a specific hour, say 7pm on Tuesday, we have decision alternatives such as 1) showing *Batman Begins* and *The Interpreters*, 2) showing *Star Wars Episode III* and *The Interpreters*, and 3) showing *Batman Begins* only. While we may still be able to rank different decision alternatives by the numbers of titles in the choice sets, the order among decision alternatives involving the same number of titles is not readily apparent. For example, before applying a model to the data, we do not know if the decision alternative of showing *Batman Begins* and *The Interpreters* within the hour of 7pm is better than the decision alternative of showing *Star Wars Episode III* and *The Interpreters*. In summary, the decision of choice set is an important but under-researched area for marketing response models. We believe our demand model can shed light on difficulties usually associated with models handling these unique types of marketing decision variables.

As mentioned, there are relatively few demand models for service scheduling in particular and models for choice set decision in general. A notable exception is the market response model in SilverScreener (Swami, Eliashberg and Weinberg 1999; Eliashberg, Swami, Weinberg and Wierenga 2001), a marketing decision support system used by multiplex movie theater managers in the Netherlands to both select and assign movies to specific screens each week. By the afternoon of each Monday, theater managers must finalize their decision concerning movies to be shown for the week starting on the next Thursday (or next Friday for the U.S. exhibitors), and must assign the chosen movies to different screens. SilverScreener helps make these decisions in two steps. First it uses a market response model to project the total weekly box office revenue for each movie if the movie is shown in a particular theater. These projected weekly revenues are then used in an optimization algorithm to choose the movies with the highest projected gross profits and assign the chosen movies to the screens, minimizing the possibility of capacity constraint. Note that SilverScreener abstracts away from the micro-scheduling issue, namely when and how frequently the theater should actually show the selected movies on a chosen day of the week. This micro-scheduling issue is essentially the choice set decision, upon which our demand model focuses. As micro-scheduling is not the purpose of SilverScreener, its market response model does not capture the underlying time preferences of moviegoers and does not consider the possible cannibalization and market expansion effects of adding or subtracting movie titles to a specific choice occasion. Our demand model therefore extends the market response model of SilverScreener to capture a richer set of moviegoer behaviors.

Beyond marketing, our demand model for service scheduling is also related to the literature of yield management and revenue management (see McGill and Van Ryzin 1999 for a literature review of both operation management and economics). Studied extensively in the airline reservation context, revenue management is the practice of controlling the availability and pricing of travel seats in different booking classes with the goal of maximizing expected revenues or profits. However, the present essay will not incorporate retail prices in its demand model nor model explicitly the truncation by capacity constraints, because our empirical application – that of multiplex movie theaters – does not change retail prices across alternatives of different qualities, and rarely encounters excess demand. We leave the incorporation of both retail pricing decision variables and service time scheduling in an integrated demand model for future research.

2.2 Discrete Choice Models with Market Level Data

Another literature stream to which our demand model relates is that of discrete choice demand models using aggregate market level data. As will be discussed in the next section, our demand model assumes that individual moviegoers' choice outcomes can be aggregated as the market shares of individual movie screenings. In marketing, there is a long tradition of using market share models to study various marketing problems (see Cooper and Nakanishi 1988). While these market share models work very well in cases characterized by stable market sizes, they cannot handle possible substitutions consumers make between a product and an alternative solution, one which is totally outside the defined product market. In other words, the primary demand expansion is assumed away. In order to capture such a potential demand expansion effect, this essay therefore adopts a setup used widely in demand models of empirical industrial organization and more recent marketing literature: specifying an outside option for each choice occasion. This specification not only captures both primary demand and substitution among different choice alternatives under a single utility maximization framework, but also greatly simplifies the estimation complexity of demand models. Specifically, as demonstrated by Berry (1994), we can invert the market shares to linearize the utility of individual choice alternatives.

As mentioned in the previous section, our demand model is similar to Einav's (2003) study of weekly seasonality in U.S. box office revenues. Also using Berry's inversion method, Einav's model specifies that the outside option should vary across different weeks of a year. Specifically, Einav hypothesizes that movie studios actually release their highest quality movies in certain weeks, which do not necessarily overlap with the weeks with highest seasonality. To distinguish empirically the weekly seasonality from the movie set variation confounded with unobserved quality perception, he specifies two structures in his discrete choice model. First, he assumes that the unobserved quality perception of each movie can be completely characterized by a movie-specific fixed effect parameter and a weekly decay factor that is constant across all movies. As these two parameters stay constant across different weeks for a movie, Einav can then pool observations of different weeks to estimate these two observation-invariant parameters and attribute the remaining weekly variability to weekly seasonality. Second, he assumes that each week of a year has its own base demand level and therefore uses 56 parameters to completely characterize the weekly seasonality and several holiday effects.

Our demand model improves on Einav's model in three aspects. First, we broaden our focus from weekly seasonality to two additional layers of seasonality, time of day and day of week. And we do this at the level of one multiplex movie theater, which is more micro than the level of the whole U.S. market. Second, in order to identify the 56 parameters for weekly seasonality, Einav must restrict all movies to having the same weekly decay rate. As our data are at a more micro level, we can allow each movie title to retain its unique weekly decay rate. We will return to this point when we discuss model specification. Third, in order to distinguish between cannibalization and market expansion, we relax Einav's assumption of IIA by exploring two model specifications, namely the nested logit and Ackerberg and Rysman's (2002) congestion specification.

To facilitate the discussion of the nested logit and Ackerberg and Rysman's (2002) specifications, we first review the notion of IIA and its implication for situations where the choice sets vary across choice occasions. In a choice set, C, which consists of alternative 1, ..., j, ... J, define the utility for alternative j as:

$$U_j = V_j + \varepsilon_j, \quad (1)$$

where V_j is the deterministic component and ε_j is the random component.

By assuming ε_j i.i.d. Gumbel (0, μ) for all j, we can derive the logit model. (Refer to Ben-Akiva and Lerman 1985, p104-107 for detailed derivation):

The probability of choosing alternative j, $P(j) = \dfrac{e^{\mu V_j}}{\sum_{h \in C} e^{\mu V_h}}$ (2)

If we compare the choice probabilities of two alternatives, say j and l, we can see the ratio of the two probabilities is entirely unaffected by any other alternatives:

$$\frac{P(j)}{P(l)} = \frac{e^{\mu V_j}}{e^{\mu V_l}} = e^{\mu(V_j - V_l)}$$

This property of logit models is called Independence of Irrelevant Alternatives (IIA). Note that this property is mainly driven by the assumption that ε_j is independently distributed across all j.

Using an example from our multiplex movie theater context, we now illustrate the implication of IIA when there is variation in choice sets across different choice occasions. Suppose there are two movies, a and b, plus an outside option. The utilities of these three alternatives are defined as:

Movie a: $U_a = V_a + \varepsilon_a$

Movie b: $U_b = V_b + \varepsilon_b$

Outside option: $U_o = V_o + \varepsilon_o$

While V_a, V_b, and V_o are the systematic components, ε_a, ε_b, and ε_o are the random components. For convenience of illustration, suppose $V_a = V_b = V_o$.

To derive a logit model, we assume ε_j is i.i.d. Gumbel (0, μ) across j, for $j = a, b, o$. Consider two choice occasions:

Occasion 1: Only Movie a starts within the time slot

$P(a) = P(o) = 1/2$ (3)

Occasion 2: Movie a and b start within the time slot

$$P(a) = P(b) = P(o) = 1/3 \tag{4}$$

As the difference between these two choice occasions is the addition/subtraction of movie b to/from the choice set, (3) and (4) together imply that the addition/subtraction of movie b affects movie a and the outside option equally. This is rather counterintuitive, as we would expect movie b to substitute more toward another movie than to the outside option. Note that under occasion (2), the substitution of movie b to the outside option essentially captures the demand expansion effect (attracting new moviegoers), while the substitution of movie b to movie a is the cannibalization effect: (prompting moviegoers to switch from movie *a)*. To restate the implication, the addition/subtraction of a movie to/from a choice set generates equal levels of demand expansion and cannibalization effects. This implication is indeed more general than our example: one can show that, in accordance with IIA, the addition/subtraction of a movie to/from a choice set affects all existing movies and the outside option equally. In other words, IIA a priori assumes the demand expansion and cannibalization effects indistinguishable.

To gain more insight into the implications of IIA on choice set variation, we follow Ben-Akiva and Lerman's (1985, p.300-304) discussion of inclusive values in re-examining occasion (2) of our example. We define the expected utility from choosing either movie a or b as:

$$U^* = \max(U_a, U_b) = V^* + \varepsilon^*$$

With the assumption that ε_i is i.i.d. Gumbel $(0, \mu)$ across movie a, b and outside option and the properties of Gumbel distribution, we can show that the systematic component of U^*,

$$V^* = \frac{1}{\mu}\ln(e^{\mu V_a} + e^{\mu V_b}) \tag{5}$$

and the random component, ε^*, is Gumbel distributed with parameters $(0, \mu)$. The discrete choice literature (e.g., McFadden 1978) typically calls V^* the "inclusive value" as it is essentially a scalar summary of the expected "worth" of all choice alternatives included in a subset of the choice set (movie a and b in our example).

Examining (5), we can see that V^* of the logit model contains an overestimate. As $V_a = V_b = V_o$ in our example, (5) can be re-written as:

$$V^* = \frac{1}{\mu}\ln 2 + V_a \tag{5a}$$

If movies a and b are perfectly correlated (e.g., different showings of the same movie title), the utility of watching either movie should be equal to $U_a = V_a + \varepsilon_a$ by intuition. Comparing this intuitive expression to U^*, which is defined as the expected utility of watching either movie, we see that our i.i.d. assumption for ε_j makes V^* too high by an amount equal to $(1/\mu)\cdot\ln(2)$. In fact, if we correct this overestimate in V^*, we obtain more intuitive probabilities for occasion (2) than (4):

$$P(a \text{ or } b) = P(o) = 1/2 \tag{6}$$

In other words, when movies a and b are perfectly correlated, the addition of movie b in occasion (2) would completely substitute toward movie a and not affect the outside option at all. To restate this in terms of cannibalization and demand expansion, when a and b are perfectly correlated, the addition of movie b in occasion (2) would only cannibalize movie a, without gaining any demand expansion.

What if the "inside" choice alternatives (those other than the outside option) are not perfectly correlated but only somewhat correlated? When the inside choices are correlated, we expect adding a new inside choice alternative to generate more cannibalization than market expansion. As standard logit models are restricted to equal cannibalization and demand expansion effects, they are not appropriate for this situation. Essentially, we must correct the overestimate in V^* discussed above. However, as the inside choice alternatives are not perfectly correlated, the overestimate is no longer precisely $(1/\mu)\cdot\ln(2)$ and we cannot correct it by simply subtracting $(1/\mu)\cdot\ln(2)$ from V^*. We evaluate two approaches to correct for the overestimate in this situation: nested logit models and Ackerberg and Rysman's (2002) congestion model.

While both approaches essentially perform the same function of correcting the overestimate in the inclusive values over all inside alternatives, they extend logit models by introducing different model structures. As discussed in Ben-Akiva and Lerman (1985, ch.10), nested logit models differ from logit models in their distributional assumption for ε_j, the random component in the utility. Specifically, nested logit models assume that ε_j for each choice alternative can be decomposed into subcomponents, and that similar choice alternatives share one or two subcomponents. By assuming each subcomponent to be Gumbel distributed with a unique scale parameter, μ, nested logit models use these different Gumbel scale parameters to correct for the overestimate in the inclusive values. Specifically, if we model our earlier example as a nested logit, we decompose ε_a and ε_b into:

$$\varepsilon_a = \varepsilon_m + \varepsilon_{a'}$$

$$\varepsilon_b = \varepsilon_m + \varepsilon_{b'}$$

where ε_m is the random component common to all choice alternatives in a subset, C_m (i.e. "watching movies" in our example), and $\varepsilon_{a'}$ and $\varepsilon_{b'}$ are the random components unique to specific movies. We essentially group all movies into a subset of "watching movies". As the outside option forms its own subset, we do not need to decompose its random component, ε_o. To derive a nested logit model, we assume: 1) ε_m, $\varepsilon_{a'}$ and $\varepsilon_{b'}$ are independent; 2) $\varepsilon_{a'}$ and $\varepsilon_{b'}$ i.i.d. Gumbel (0, μ'); and 3) ε_m and ε_o are distributed so that ε_o and $\varepsilon_m + \varepsilon_j$ for $j = a'$ and b' are independently Gumbel distributed with scale parameter μ^m. The choice probabilities in occasion (2) are then:

$$P(j) = \frac{e^{\mu^m (V_m^*)}}{e^{\mu^m (V_o)} + \sum_{h \in Cm} e^{\mu^m (V_m^*)}} \quad \text{for } j = a \text{ or } b \tag{7}$$

$$\text{where } V_m{*} = \frac{1}{\mu'}\ln(e^{\mu' V_a} + e^{\mu' V_b}) \tag{8}$$

$$P(o) = \frac{e^{\mu^m (V_o)}}{e^{\mu^m (V_o)} + \sum_{h \in Cm} e^{\mu^m (V_m{*})}} \tag{9}$$

Note that $V_m{*}$ is essentially the inclusive value for the alternatives in the subset C_m or the expected utility of choosing either movie *a* or *b*. At first glance, the inclusive value in the nested logit, (8), is identical to its counterpart in the standard logit, (5), only with a different scale parameter, μ or μ', suggesting that nested logit models may suffer from the same type of overestimate as logit models. However, note that μ in logit models is empirically non-identifiable and therefore is usually set to one during estimation. On the other hand, while μ^m in nested logit models is also empirically non-identifiable, μ' is actually identifiable. In other words, μ' serves as the parameter to rescale the inclusive value such that the overestimate in the logit model can be somewhat corrected.

We illustrate how the rescaling works in our example. In the case in which movies *a* and *b* are highly correlated, the variance for the Gumbel distribution of $\varepsilon_{a'}$ and $\varepsilon_{b'}$ should be very small, and the scale parameter, μ', which is inversely related to the variance, is therefore very large. In the extreme case that μ' tends to infinity, according to the line of proof in Ben-Akiva and Lerman (1985, p.309-310), the inclusive value, $V_m{*}$, would tend to $\max(V_a, V_b)$. As $V_a = V_b = V_o$ in our example, when movies *a* and *b* are almost identical, $V_m{*}$ will tend to V_a, and both *P(a or b)* and *P(o)* therefore tend to 1/2, which is in line with our intuition that the addition of movie *b* completely cannibalizes movie *a* but does not attract new customers from the outside option.

We now consider the second approach for distinguishing cannibalization and demand expansion when there is choice set variation. While Ackerberg and Rysman (2002) do not interpret their congestion model with the notion of inclusive values, we illustrate here that their basic tenet is also to correct for the overestimate in the inclusive value of the standard logit model. In fact, by considering Ackerberg and Rysman's [AR] model from such a perspective, we can easily compare their model structures to the nested logit's. More specifically, unlike nested logit models, which focus on modifying the random utility component of standard logit models, ε_j, AR model essentially introduces a correction factor to the systematic component, V_j. In our earlier example, if movies a and b are perfectly correlated, $(1/\mu)\cdot\ln(2)$ is precisely the overestimate in the inclusive value, V^*, and we therefore should add a correction factor equal to $-(1/\mu)\cdot\ln(2)$ to each of V_a and V_b. In a more general case in which there are J perfectly correlated movies, the corresponding inclusive value, denoted as $V^{*\prime}$, is:

$$V^{*\prime} = \frac{1}{\mu}\ln\left(\sum_{j=1}^{J} e^{\mu V_j}\right) \tag{10}$$

For convenience of illustration, suppose the systematic component, V_j for all $j = 1, \ldots, J$ are equal. $V^{*\prime}$ can be rewritten as:

$$V^{*\prime} = \frac{1}{\mu}\ln(J) + V_J \tag{10a}$$

Similar to the argument in the two-movie case, the more intuitive value of the inclusive value or the expected utility of choosing one of the perfectly correlated movies is simply V_J. In other words, the independent random component assumption in standard logit models makes $V^{*\prime}$ too large by the amount equal to $(1/\mu)\cdot\ln(J)$. If we want to correct for this overestimate, we should add a correction factor equal to $-(1/\mu)\cdot\ln(J)$ to each of the systematic component, V_j for all $j = 1, \ldots, J$.

In an even more general case in which the J movies are not perfectly correlated, we no longer know precisely what the correction factor should be. However, from the perfect correlation case, we know that the correction factor is related to the number of inside choice alternatives, J. We therefore can let the data tell us how much to correct by specifying the correction factor as a function of J, $f(J;\gamma)$, where γ is a vector of parameters to be estimated from the data. This is precisely the specification of AR additive model. Note that with the exception of adding the correction factor to the systematic utility component, AR model is a standard logit model.

Consider one of the specifications of $f(J;\gamma)$ proposed by AR model: $\gamma\ln(J)$. Back to our two-movie example, the correction factor is then equal to $\gamma\ln(2)$. Given that we set the non-identifiable μ at one during estimation, if movies a and b are perfectly correlated, the data would estimate γ to be -1, which makes $\gamma\ln(2)$ equal to the required correction.

In summary, both the nested logit model and AR congestion model share the same conceptual underpinning: to correct the overestimate in the inclusive value of standard logit models. However, there are two main differences between the two. First, they use different model structures to correct for the overestimate. While the nested logit model focuses on the random utility component, AR model works with the systematic utility component[3]. Second, AR model allows more flexibility to approximate the required correction by specifying a different functional form for $f(J;\gamma)$. For example, a quadratic form for $f(J;\gamma)$ is more flexible. Compared to the single parameter (μ in nested logit models), the two parameters of the quadratic form provide more flexibility in characterizing the required correction. On the other hand, as stated as the property of "monotonicity with respect to choice set size" by Ben-Akiva and Lerman (1985, p.301), nested logit model does not allow total shares of all inside alternatives to decrease as more choice alternatives are added. However, AR model has enough flexibility to allow the data to exhibit this pattern.

[3] Note that in Ackerberg and Rysman (2002) and our later model development section, the congestion models are in fact motivated by making an additional assumption for the random utility component. However, this additional assumption does not change any underlying distributional assumptions for the random component and in effect affects only the systematic utility component.

3. Model Development

We now develop three demand models for multiplex movie theaters. The first is a base model used to illustrate how moviegoers' underlying time preferences can be disentangled from unobserved product quality. Next, to distinguish between the cannibalization and market expansion effects when there is choice set variation across choice occasions, we develop a nested logit model and a variant of AR congestion model.

3.1 Base Model

We seek to identify three layers of time preference from the aggregate attendance data: systematic variations across different times of day, different days of the week and different times of year. We call these three layers of systematic variations time of day, day of week and time of year seasonality, respectively. At first glance, these three seasonality layers appear to be easily identifiable through a simple examination of the hourly pattern of historical attendance data. For example, we can generate cross-tables of admission per showing by each hour, by each day of the week and by each week. Table-1a, 1b and 1c show such cross-tables for one of our samples, which contains the admission records of all movie screenings at a multiplex movie theater in Amsterdam, the Netherlands from January 4, 2001 to April 18, 2001.

Let us start with time of day seasonality. We can see from Table-1a that movie showings starting in the hour beginning at 9pm tend to attract the highest admission numbers. One may therefore assume that the hour of 9pm is the most preferable time slot in which to watch movies at the focal multiplex movie theater. However, one should also note that the number of showings is unevenly distributed across different hours. For example, there were 820 movie showings starting in the hour of 9pm, but only 252 movie showings starting in the hour of 8pm. This uneven distribution suggests that the same set of movies does not start in each hour. In other words, one movie title may start in one hour but not the other. If there is a systematic relationship between a specific hour and perceived quality of movies, the seasonality pattern revealed by Table-1a may be susceptible to substantial bias. For example, due to habit or a belief in a certain myth, suppose that a theater manager has a tendency to select the highest quality movies for the 9 pm time slot. The movie choice set variation across hours will then be confounded with the perceived quality variation. When we observe from a historical data set that movie showings starting in the hour of 9 pm generate the highest average attendance, as suggested by Table-1a, it is difficult to determine whether this is due to the fact that moviegoers had the strongest preference for the 9 pm time slot, or due to a confounding between movie set variation and perceived quality. To complicate things further, the ways in which moviegoers perceive the quality of each movie are unobservable to us researchers and analysts (but may have been observable to theater managers at the time they scheduled the movies), and it is likely that these unobserved qualities change over time and therefore vary across observations. In other words, each observation has a unique unobservable component, which may be confounded with the seasonality in which we are interested. Our solution to this problem is to impose a parsimonious specification on how unobserved movie quality varies over time. We then assume that all remaining variability across time and across observations is the result of seasonality and white noise. In fact, after controlling for such a confounding issue, our demand model suggests 8pm, rather than 9pm, is the most preferred start time for moviegoers at the multiplex movie theater in Amsterdam.

Table-1b suggests that movie screenings on Saturday and Sunday tend to attract the largest admission figures. Unlike the circumstance related to time of day seasonality, it is unlikely that the set of movies would vary greatly across different days of the week.[4] In fact, the rather stable numbers of showings across different days of a week in Table-1b are consistent with the industry practice that theater managers have a fixed set of movies to be shown for the whole week, while the set may vary greatly across weeks. In other words, we expect the day of week pattern revealed by a simple cross-table to remain unchanged in our demand model.

Finally, Table-1c demonstrates time of year seasonality. Specifically, movie showings during the week of March 1-7, 2001 tend to attract most moviegoers. Note that this week overlaps with the spring vacation for secondary schools in Amsterdam (March 3-11, 2001), therefore suggesting a school holiday effect. As the sets of movies shown vary greatly across weeks, it is possible that the holiday effect is confounded with movies of higher perceived quality. Therefore, after controlling for the unobserved movie quality, our demand model may estimate insignificant holiday effects.

Our modeling approach is to model demand as an aggregation of individuals' discrete choices. In line with other discrete choice models using aggregate level data, we assume that there are a finite number of potential moviegoers, *N*, for our multiplex movie theater, and that each of the potential moviegoers consumes at most one movie showing within a chosen time frame. To simplify our three models, and for ease of exposition, the present essay assumes that the time frame for the unit demand restriction is one hour. We recognize that it is unlikely that an individual moviegoer would consume in the next hour with the same probability another unit of the same movie. However, while we may not capture the richer details of moviegoer behaviors, the setting is certainly sufficient for studying the three layers of seasonality in which we are interested and to serve as a clean platform for comparison of the nested logit and AR models. We therefore leave the exploration of other time frame assumptions for future research.

[4] In our data sets, for every week the same set of movies was shown every day from a Thursday to the following Wednesday. The only exception was that few children's movie titles were shown only as the matinees on weekdays.

To derive our base model, we first introduce the notations:

d = Date a movie is shown

h = Hour a movie starts (e.g. 10 am – 10 pm)

TP_d = Average temperature on date d

DR_d = Precipitation duration on date d

$HD1_d$ = Indicator variable for the event that date d falls during the spring vacation

$HD2_d$ = Indicator variable for the event that date d falls during the May vacation

$HD3_d$ = Indicator variable for the event that date d is Ascension Day

$HD4_d$ = Indicator variable for the event that date d is Whit Sunday or Whit Monday

$HD5_d$ = Indicator variable for the event that date d falls on the Easter weekend

$HD6_d$ = Indicator variable for the event that date d falls during the summer vacation

$HD7_d$ = Indicator variable for the event that date d falls during the fall vacation

$HD8_d$ = Indicator variable for the event that date d falls during the Christmas vacation

MON_d = Indicator variable for the event that date d is Monday

TUE_d = Indicator variable for the event that date d is Tuesday

WED_d = Indicator variable for the event that date d is Wednesday

THU_d = Indicator variable for the event that date d is Thursday

FRI_d = Indicator variable for the event that date d is Friday

SAT_d = Indicator variable for the event that date d is Saturday

SUN_d = Indicator variable for the event that date d is Sunday

$I_{\{j\}}$ = Indicator variable for the event that movie j is being shown

$I_{\{h\}}$ = Indicator variable for the event that the movie starts within hour h

$SUNPM$ = Indicator variable for the event that the movie starts on Sunday between the hour of 2pm to 6pm

A_{jd} = Age of movie j on date d (number of weeks since movie j's release week)

We now specify potential moviegoer i's utility for the outside good in hour h on date d:

$$
\begin{aligned}
U_{i0hd} &= -\tau_{hd} + \varepsilon_{i0hd} \\
&= -(\omega_0 + \omega_{TP}\cdot TP_d + \omega_{DR}\cdot DR_d + \omega_{HD1}\cdot HD1_d + \omega_{HD2}\cdot HD2_d + \ldots + \omega_{HD8}\cdot HD8_d \\
&\quad + \omega_{MO}\cdot MON_d + \ldots + \omega_{SU}\cdot SUN_d + \sum_{\forall h}\beta_h \cdot I_{\{h\}} + \omega_{SUNPM}\cdot SUNPM) + \varepsilon_{i0hd} \qquad (11)
\end{aligned}
$$

where $-\tau_{hd}$ is the systematic utility component of the outside option in hour h on date d and ε_{i0hd} is the unobserved utility component facing individual i in hour h on date d.

Potential moviegoer i's utility for movie j starting in hour h on date d:[5]

$$
\begin{aligned}
U_{ijhd} &= \delta_{jd} + \xi_{jhd} + \varepsilon_{ijhd} \\
&= \sum_{\forall j}\theta_j \cdot I_{\{j\}} + \lambda_j\cdot A_{jd} + \xi_{jhd} + \varepsilon_{ijhd} \qquad (12)
\end{aligned}
$$

where δ_{jd} is the systematic utility component of movie j on date d, ε_{ijhd} is the unobserved utility component of movie j starting in hour h on date d, specific to individual i; and ξ_{jhd} is the unobserved utility components of movie j starting in hour h on date d, common to all individuals. We may interpret ε_{ijhd} and ε_{i0hd} as taste variation across individuals. However, unlike Hotelling's horizontal differentiation framework, we actually do not observe the ways in which different choice alternative j's are differentiated from one another (i.e. their location on the unobserved product space is unobservable). Such unobservablility keeps us from capturing precisely the notion that an individual's address will lead her to prefer a choice alternative located in her neighborhood and to dislike a remotely located alternative. In other words, the negative correlation of an individual's preferences towards different products cannot be characterized here.

[5] Note that we cannot identify all the parameters in (11) and (12) at the model estimation stage. For example, we need to drop Saturday in order to estimate the "parameter differences" between other weekdays and Saturday. Also note that by normalization, we can move all variables in U_{i0hd}, (11), including the intercept ω_0, to U_{ijhd}, (12).

The three layers of seasonality are captured by three sets of parameters in (11). First, ω_{HD1}, ω_{HD2}, ω_{HD3}, ..., ω_{HD7} and ω_{HD8} capture the time of year effect. In particular, as people tend to have more free time for leisure activities such as going to movie theaters during holidays or school vacations, as compared to normal work or school days, we expect all of these parameters to be positive and therefore to make the outside option less attractive (due to the negative sign of U_{i0hd}). The eight holiday indicator variables are chosen to primarily represent the holidays and vacations taken by secondary school students in Amsterdam, as they represent the main target market for the focal multiplex movie theater, according to the theater managers. Five school vacation periods, namely spring, May, summer, fall and Christmas vacations are therefore identified first. Three public holidays outside these vacation periods, namely Ascension Day, Whit weekend and Easter weekend are then added to capture the other potential holiday effects. The second layer of seasonality is the day of week effect. Seven parameters ω_{MO}, ω_{TU}, ω_{WE}, ω_{TH}, ω_{FR}, ω_{SA} and ω_{SU} capture such seasonality. As students and adults must skip work or school to watch a movie on a normal weekday, we expect ω_{MO}, ω_{TU}, ω_{WE}, ω_{TH} and ω_{FR}, the parameters for the five weekdays, to be smaller than ω_{SA} and ω_{SU}, the parameters of the weekends, so as to reflect the higher opportunity costs on a weekday. Finally, β_h's capture the time of day effect. Similar to the above argument, students and adults on a normal weekday tend to have higher opportunity costs (learning or wage) during the daytime and prefer to watch movies in the evening. Moreover, even during weekends, people tend to have more activities other than movie-watching during the daytime than in the evening (e.g., outdoor activities). We therefore expect the β_h's corresponding to the daytime to be smaller than those for the evening.

The present essay also explores a potential interaction effect among different layers of seasonality, namely the Sunday afternoon effect. Table-2a, 2b, 2c, 2d, 2e, 2f and 2g are cross-tables of the admission figures per showing by each hour across all Sundays, all Mondays, all

Tuesdays, all Wednesdays, all Thursdays, all Fridays and all Saturdays of our 2001 sample discussed earlier. Examining these tables carefully, we can see roughly the same time of day pattern across different days of a week, with the exception of Sunday (Table-2a). Unlike other days, movie screenings starting Sunday afternoon (between the hours of 2pm and 6pm) tend to attract more admission than those in the evening, suggesting a deviation from the time of day pattern of other days. ω_{SUNPM}, the parameter associated with *SUNPM*, is intended to capture this deviation. We expect ω_{SUNPM} to be positive.

Note that in addition to capturing two more layers of seasonality, our model also differs from Einav's (2003) in the way the time of year is characterized. As discussed earlier, Einav assumes each week of a year has a unique base demand, and therefore characterizes the time of year seasonality with 56 parameters (52 weekly parameters plus 4 major holidays, which move around in the calendar). We decided not to follow Einav's specification for two reasons. First, as we will discuss in the data description section, both of our data samples are shorter than one year. In other words, for any of the 52 weeks, we do not have any replication of the same week of another year. It is therefore difficult to estimate reliably the average effect of each of the 52 weeks. On the other hand, if we assume the base demand level would deviate from other times of year only on holidays or school vacations (some of which span longer than a week), we would have more movie showings in the base group as well as in different holiday groups, and the estimated time of year pattern would therefore be relatively more reliable. Second, as argued by Pierce, Grupe and Cleveland (1984), the use of weekly fixed effect parameters to capture time of year seasonality is not very satisfactory, for two main reasons. First, many holidays occur in different weeks of different years. Although Einav attempts to address the second concern by allowing additional parameters to capture the "moving" holidays, this specification essentially increases more parameters, which are even harder to estimate reliably with our "less-than-a-year-long data sets". Second, there is not an integral or even a constant number of weeks in the year: 52 $\frac{1}{7}$ weeks in most years and 52 $\frac{2}{7}$ weeks in leap year.

In addition to the variation across time, we also assume the outside option to vary with two weather variables, namely average daily temperature, TP_d, and total daily precipitation (rain or snow) duration, DR_d. Unlike the seasonality parameters, we do not offer an a priori prediction on how the weather may affect the attractiveness of the outside option.

As discussed in the beginning of the section, in order to identify the underlying time preferences of moviegoers, we must control for the unobserved movie quality. The unobserved quality of individual movies is captured with a movie-specific parameter, θ_j, and a movie-specific weekly decay factor, λ_j. As shown in (12), we structurally restrict U_{ijhd} to vary across time only through λ_j, and the unobserved quality of each movie is assumed to be characterized completely by λ_j and θ_j. Under this model specification, all remaining variation in the aggregated demand is due to white noise and seasonality only. Choice outcomes across different weeks can therefore be pooled together to increase the number of observations and identify all parameters in the model.

Einav (2003) actually imposes an identification restriction stronger than ours. In particular, he restricts the weekly decay parameter, λ, to be common to all movies, or at best to be specific to a particular movie genre. The reason we can estimate a movie-specific decay parameter, λ_j, lies in the fact that our unit of observation- admission for each movie showing- is more micro than Einav's. While Einav relies only on one observation per week per movie title to identify both λ and his 56 weekly seasonality parameters, we have by and large 30 observations per week per movie title. Moreover, our simpler specification of time of year seasonality also gives us more degrees of freedom to identify the movie-specific decay parameters and the holiday parameters.

By assuming that moviegoer heterogeneity in taste, ε_{ijhd} and ε_{i0hd}, are independently and identically distributed Gumbel (0,1), we can derive the multinomial logit hourly shares for individual movies and the outside option:

For movie $j \in C_{hd}$, where C_{hd} is the set of movies starting within hour h on date d, the share of movie j starting in hour h on date d,

$$s_{jhd} = \frac{\exp(\delta_{jd} + \xi_{jhd})}{\exp(-\tau_{hd}) + \sum_{k \in C_{hd}} \exp(\delta_{kd} + \xi_{khd})} \tag{13}$$

The share of the outside option,

$$s_{0hd} = \frac{\exp(-\tau_{hd})}{\exp(-\tau_{hd}) + \sum_{k \in C_{hd}} \exp(\delta_{kd} + \xi_{khd})} \tag{14}$$

Following Berry's (1994) inversion method, we transform and rearrange (13) and (14) to obtain:

$$\ln(s_{jhd}) - \ln(s_{0hd}) = \tau_{hd} + \delta_{jd} + \xi_{jhd} \tag{15}$$

By assuming that ξ_{jhd} is normally distributed and i.i.d. across j, h and d, we can estimate (15) by OLS.[6]

3.2 Nested Logit Model

Essentially a standard logit model, the base model always predicts that a new movie title added to an existing choice set will substitute the outside option and other movie titles equally, making the cannibalization and market expansion effects indistinguishable. As discussed earlier,

[6] One may compare (15) to a model regressing ln(attendance of movie j in hour h on date d) against the same right-hand side variables of (15). As the right-hand side specification is the same, such a regression model will also allow us to identify both the unobserved movie quality and seasonality. The problem is that it abstracts away from the substitution among different showings and the outside option. As another objective of our demand model is to characterize cannibalization among different movie choices and market expansion, the underlying discrete choice notion of (15) serves as a better foundation from which to extend the base model.

the nested logit model and AR model are the two specifications that can address this issue. We therefore develop a nested logit model from the base model in this subsection.

Following the specification of the base model, we define the utilities for the outside option and for movie j starting in hour h on date d as below:

Potential moviegoer i's utility for the outside good within hour h on date d:

$$\begin{aligned} U_{i0hd} &= -\tau_{hd} + \varepsilon'_{i0hd} \\ &= -(\omega_0 + \omega_{TP}\cdot TP_d + \omega_{DR}\cdot DR_d + \omega_{HD1}\cdot HD1_d + \omega_{HD2}\cdot HD2_d + \ldots + \omega_{HD8}\cdot HD8_d \\ &\quad + \omega_{MO}\cdot MON_d + \ldots + \omega_{SU}\cdot SUN_d + \sum_{\forall h}\beta_h \cdot I_{\{h\}} + \omega_{SUNPM}\cdot SUNPM) + \varepsilon'_{i0hd} \end{aligned} \tag{16}$$

where ε'_{i0hd} is the unobserved utility component of the outside option facing individual i in hour h on date d.

Potential moviegoer i's utility for movie j starting in hour h on date d:

$$\begin{aligned} U_{ijhd} &= \delta_{jd} + \xi_{jhd} + \nu_{ihd} + (1-\sigma)\cdot\varepsilon'_{ijhd} \\ &= \sum_{\forall j}\theta_j \cdot I_{\{j\}} + \lambda_j\cdot A_{jd} + \xi_{jhd} + \nu_{ihd} + (1-\sigma)\cdot\varepsilon'_{ijhd} \end{aligned} \tag{17}$$

where ν_{ihd} is the unobserved utility component common to all movies in hour h on date d, specific to individual i, while ε'_{ijhd} is the unobserved utility component specific to movie j in hour h on date d, specific to individual i.

Note that the systematic components of U_{i0hd} and U_{ijhd} in the nested logit model, (16) & (17), are identical to those in the standard logit model, (11) & (12). We therefore maintain the feature of disentangling the underlying time preference and unobserved movie quality in the nested logit model. The point of departure is the specification of random components. Specifically, we decompose the random component of U_{ijhd} into two subcomponents, ν_{ihd} and ε'_{ijhd}. While ν_{ihd} is common to all movie titles in hour h on date d, ε'_{ijhd} is unique to each movie title. In the terminology of the nested logit model literature, we essentially define two nests in the choice set of each hour. One is a nest of movie choices and the other is the outside option, which is the sole element in its nest. Therefore, ν_{ihd}, together with ε'_{i0hd}, represent the randomness at the level of choosing which nest, and ε'_{ijhd} represents the randomness of each movie choice within the nest of movie-watching. We can interpret this specification intuitively. Individual i incurs the same amount of random utility ν_{ihd} if choosing any movie available at the focal multiplex movie theater at the time, and by choosing a specific movie j, s/he then also obtains ε'_{ijhd}, an additional amount of utility unique to movie j.

Although we followed Ben-Akiva and Lerman's (1985) notation when reviewing the distributional assumptions of nested logit models earlier, we now switch to Cardell's (1997) notations, as these can simplify the exposition when we use Berry's (1994) inversion method later. Specifically, we assume: 1) ν_{ihd} and ε'_{ijhd} are independently distributed; 2) ε'_{ijhd} i.i.d. Gumbel (0, 1); and 3) ν_{ihd} and ε'_{i0hd} are distributed so that ε'_{i0hd} and $[\nu_{ihd} + (1-\sigma)\cdot\varepsilon'_{ijhd}]$ are independently Gumbel (0,1).[7] Note that $(1-\sigma)$ is the variance component within the nest of movie-watching and $0 \leq \sigma \leq 1$. As σ approaches one, the within-nest correlation of different choice utilities goes to one. Intuitively, when σ is close to one, individual i essentially perceives all available movies in the same way (all movies are perfectly correlated). On the other hand, if σ is smaller than one, individual i exhibits some unobserved taste variation across different movie titles.

For movie $j \in C_{hd}$, we can integrate ν_{ihd}, ε'_{ijhd} and ε'_{i0hd} over all individuals i in hour h on date d to obtain the following share expressions:

[7] One can reconcile this notation with the notation we used in our earlier example: $(1-\sigma)$ is the inverse of the scale parameter, μ', and we set μ^m to be one.

The share of movie j starting in hour h on date d, on the condition that a movie from C_{hd} is chosen,

$$s_{jhd|C_{hd}} = \frac{\exp((\delta_{jd} + \xi_{jhd})/(1-\sigma))}{\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))} \tag{18}$$

The total share of all movie titles in C_{hd},

$$s_{C_{hd}} = \frac{[\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))]^{(1-\sigma)}}{\exp(-\tau_{hd}) + [\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))]^{(1-\sigma)}} \tag{19}$$

The share of movies j starting in hour h on date d,

$$s_{jhd} = s_{jhd|C_{hd}} \cdot s_{C_{hd}} = \frac{\exp((\delta_{jd} + \xi_{jhd})/(1-\sigma))}{[\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))]^{\sigma} \cdot [\exp(-\tau_{hd}) + [\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))]^{(1-\sigma)}]} \tag{20}$$

The share of the outside option in hour h on date d,

$$s_{0hd} = \frac{\exp(-\tau_{hd})}{\exp(-\tau_{hd}) + [\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma))]^{(1-\sigma)}} \tag{21}$$

Following Berry's (1994) inversion method, we can obtain the following two expressions:

$$\ln(s_{jhd}) - \ln(s_{0hd}) = (\delta_{jd} + \xi_{jhd})/(1-\sigma) + \tau_{hd} - \sigma \cdot \ln\left(\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma)) \right) \tag{22}$$

$$\ln(s_{C_{hd}}) - \ln(s_{0hd}) = (1-\sigma) \cdot \ln\left(\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma)) \right) + \tau_{hd} \tag{23}$$

Using (23) to substitute $\ln\left(\sum_{k\in C_{hd}} \exp((\delta_{kd} + \xi_{khd})/(1-\sigma)) \right)$ out in (22) and using the fact that $s_{jhd|C_{hd}} = s_{jhd} / s_{C_{hd}}$, we get:

$$\ln(s_{jhd}) - \ln(s_{0hd}) = \delta_{jd} + \tau_{hd} + \sigma \cdot \ln(s_{jhd|C_{hd}}) + \xi_{jhd} \tag{24}$$

As $s_{jhd|C_{hd}}$ is an endogenous variable to $\ln(s_{jhd}) - \ln(s_{0hd})$, we need to estimate (24) by the two-stage least square method with instruments for $s_{jhd|C_{hd}}$. The details of the estimation will be discussed in a later section.

3.3 Crowding Model

In addition to the nested logit model, we now develop an alternative model, Ackerberg and Rysman's (2002) additive congestion model, which also can distinguish the cannibalization and market expansion effects when a new movie title is added to an existing choice set. To better understand the linkage between AR model and the logit model, we will motivate the model differently from that of Ackerberg and Rysman.

In the base model, moviegoers are assumed to have their unobserved preferences distributed over the available movie choices. Our crowding model departs from this by assuming that moviegoers have their unobserved preferences distributed over an unobserved product space, which is the building block for the available movie choices and the outside option. In particular, we assume that when a new movie choice is added to the choice set, the new choice would make such a product space more crowded and would cause the attractiveness of the existing movie choices, relative to the outside option, to decrease. Therefore, by modeling the degree of crowding of the unobserved product space, we can characterize the cannibalization relative to the market expansion effect.

To fix the idea, we denote the volume of the unobserved product space in hour h on date d to be R_{hd}. We also assume that the unobserved product space is filled with very small dots and that each dot is "owned" by either the outside option or one available movie choice. By normalization, we can set the total number of dots equal to R_{hd}. Note that our assumption does not allow any dot to be "not owned". Thus, if we denote R_{0hd} and R_{jhd} as the number of dots (or the volume of the unobserved product space), the outside option and choice alternative j occupy respectively, $\sum_{\forall j} R_{jhd} + R_{0hd} = R_{hd}$. As a new movie choice is expected to crowd out more toward other movie choices than toward the outside option, we characterize the degree of crowding among movie choices by specifying that the normalized product space, $\frac{R_{jhd}}{R_{0hd}}$, varies with J_{hd}, the number of movie choices available in hour h on date d. In particular, we expect $\frac{R_{jhd}}{R_{0hd}}$ to decrease with J_{hd}.

Denote Ω_{0hd} and Ω_{jhd} as the sets of product space dots owned by the outside option and movie j in the choice occasion of hour h on date d, respectively. As mentioned earlier, moviegoer preferences are now distributed over the unobserved product space. We can express moviegoer i's utility for a dot $r \in \Omega_{0hd}$ as:

$$\begin{aligned} U_{ir} &= -\tau_{hd} + \varepsilon_{ir} \\ &= -(\omega_0 + \omega_{TP} \cdot TP_d + \omega_{DR} \cdot DR_d + \omega_{HD1} \cdot HD1_d + \omega_{HD2} \cdot HD2_d + \ldots + \omega_{HD8} \cdot HD8_d \\ &\quad + \omega_{MO} \cdot MON_d + \ldots + \omega_{SU} \cdot SUN_d + \sum_{\forall h} \beta_h \cdot I_{\{h\}} + \omega_{SUNPM} \cdot SUNPM) + \varepsilon_{ir} \end{aligned} \tag{25}$$

Note that (25) is almost identical to (11), the utility for the outside option in the base model. Although the random component is ε_{ir}, the systematic component still varies with time of day, day of week, time of year and two weather variables.

Similarly, we can express moviegoer i's utility for a dot $r \in \Omega_{jhd}$ as:

$$\begin{aligned} U_{ir} &= \delta_{jd} + \xi_{jhd} + \varepsilon_{ir} \\ &= \sum_{\forall j} \theta_j \cdot I_{\{j\}} + \lambda_j \cdot A_{jd} + \xi_{jhd} + \varepsilon_{ir} \end{aligned} \tag{26}$$

By assuming ε_{ir} to be i.i.d. Gumbel (0,1), we obtain the share for dot $r \in \Omega_{0hd}$:

$$s_r = \frac{\exp(-\tau_{hd})}{\sum_{r\in\Omega_{0hd}}\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}\sum_{r\in\Omega_{khd}}\exp(\delta_{kd}+\xi_{khd})}$$

$$= \frac{\exp(-\tau_{hd})}{R_{0hd}\cdot\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}R_{khd}\cdot\exp(\delta_{kd}+\xi_{khd})} \quad (27)$$

Similarly, the share for dot $r \in \Omega_{jhd}$ is:

$$s_r = \frac{\exp(\delta_{jd}+\xi_{jhd})}{\sum_{r\in\Omega_{0hd}}\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}\sum_{r\in\Omega_{khd}}\exp(\delta_{kd}+\xi_{khd})}$$

$$= \frac{\exp(\delta_{jd}+\xi_{jhd})}{R_{0hd}\cdot\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}R_{khd}\cdot\exp(\delta_{kd}+\xi_{khd})} \quad (28)$$

By assuming that all the product space dots owned by a choice alternative are identical, we can aggregate the share of dot r up to the share of the choice alternative by multiplying s_r by the number of dots owned by the choice alternative.

For $r \in \Omega_{0hd}$,

$$s_{0hd} = R_{0hd}\cdot s_r = \frac{R_{0hd}\cdot\exp(-\tau_{hd})}{R_{0hd}\cdot\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}R_{khd}\cdot\exp(\delta_{kd}+\xi_{khd})}$$

$$= \frac{\exp(-\tau_{hd})}{\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}\frac{R_{khd}}{R_{0hd}}\cdot\exp(\delta_{kd}+\xi_{khd})} \quad (29)$$

For $r \in \Omega_{jhd}$,

$$s_{jhd} = R_{jhd}\cdot s_r = \frac{R_{jhd}\cdot\exp(\delta_{jd}+\xi_{jhd})}{R_{0hd}\cdot\exp(-\tau_{hd}) + \sum_{k\in C_{hd}}R_{khd}\cdot\exp(\delta_{kd}+\xi_{khd})}$$

$$= \frac{\frac{R_{jhd}}{R_{0hd}} \cdot \exp(\delta_{jd} + \xi_{jhd})}{\exp(-\tau_{hd}) + \sum_{k \in C_{hd}} \frac{R_{khd}}{R_{0hd}} \cdot \exp(\delta_{kd} + \xi_{khd})} \tag{30}$$

Similar to the derivation of the base model, we combine and rearrange (29) and (30) to obtain:

$$\ln(s_{jhd}) - \ln(s_{0hd}) = \tau_{hd} + \delta_{jd} + \ln(\frac{R_{jhd}}{R_{0hd}}) + \xi_{jhd} \tag{31}$$

Note that (31) is almost identical to (15) from the base model, except for the R_{jhd}/R_{0hd} term. Upon the specification of $\ln(R_{jhd}/R_{0hd})$, we can estimate (31) by OLS.

$\ln(R_{jhd}/R_{0hd})$ is essentially a correction factor for the overestimate of the expected utility for all available movie choices relative to the outside option. As discussed in section 2.2, an overestimate in the inclusive value over the movie choices is causing difficulty in distinguishing between cannibalization and market expansion. We also argued that the basic tenet of AR model is to introduce a correction factor into the systematic component of the utility. However, one should distinguish this basic tenet from the actual model derivation of our crowding model. In particular, note that the correction factor does not enter the systematic component directly. Instead, $\ln(R_{jhd}/R_{0hd})$ is derived from aggregating U_{ir} over all product space dots for a specific choice alternative. In fact, if we work backward from (30), we can deduce the utility for movie j starting in hour h on date d under our crowding model:

$$U_{ijhd} = \delta_{jd} + \ln(R_{jhd}/R_{0hd}) + \xi_{jhd} + \varepsilon_{ijhd} \tag{32}$$

Absent in U_{ijhd} of the standard logit model (12), $\ln(R_{jhd}/R_{0hd})$ serves as a correction factor in the systematic utility component, which can correct for the overestimate when the inclusive value for all available movie choices is computed.

We now discuss the specification of $\ln(R_{jhd}/R_{0hd})$. As mentioned earlier, to characterize the degree of crowding in the unobserved product space, we expect R_{jhd}/R_{0hd} will decrease with

J_{hd}, the number of movie choices available in hour h on date d. We explore three different functional forms for this relation:

$$R_{jhd}/R_{0hd} = (J_{hd})^{\gamma_a} \tag{33a}$$

$$R_{jhd}/R_{0hd} = \exp(\gamma_{b1} \cdot J_{hd}) \tag{33b}$$

$$R_{jhd}/R_{0hd} = \exp(\gamma_{c1} \cdot J_{hd} + \gamma_{c2} \cdot J_{hd}^2) \tag{33c}$$

As J_{hd} is non-negative, the above three specifications can ensure that the logarithm of R_{jhd}/R_{0hd} is well defined.

Note that all three specifications incorporate the standard logit model as a special case. For (33a), when γ_a is zero, $\ln(R_{jhd}/R_{0hd})$ will become zero, reducing the model to a standard logit. Similarly, when γ_{b1} is zero or when γ_{c1} and γ_{c2} are both zero, $\ln(R_{jhd}/R_{0hd})$ will become zero for (33b) or (33c). By determining if $\ln(R_{jhd}/R_{0hd})$ is zero, we can tell if the addition of new movie choices will substitute the existing movie choices and the outside option equally. In other words, instead of a priori assuming equal cannibalization and market expansion, the crowding model can tell us if this is an appropriate description of the data.

4. Data Description

We calibrate the three demand models with two data sets from a multiplex movie theater in the Netherlands. The first data set records the admissions for 5,906 movie screenings during the first 15 weeks of 2001, from January 4 to April 18.[8] The second data set spans from May 29, 2003 to June 9, 2004 (54 weeks) and records the admissions for 22,121 movie showings. As the second data set covers more than a whole year and contains a relatively large number of

[8] We define admissions here as paid admissions only; because free admissions represent a totally different moviegoer behavior and free admissions are not substantial in our two data sets: free admissions for each movie showing on average comprise only 3.15% and 4.09% of total admissions in the first and second data sets. In fact, in both data sets, only around 20% of movie showings had free admissions at a level of more than 5% of the total admissions.

observations, we can afford reserving the last two weeks of observations for validation purposes. The second data set is therefore split into two: a 52-week calibration sample of 21,341 movie showings from May 29, 2003 to May 26, 2004; and a two-week validation sample of 780 movie showings from May 27 to June 9, 2004.

Capacity constraint for each service offering and price variation across different offerings are two issues commonly encountered by pre-announced time schedule service providers when they optimize their time schedules. While critical to most service providers, these issues are relatively less important to the demand models of multiplex movie theaters. First, our multiplex movie theater in the Netherlands did not have many capacity-censored observations during the two observation windows for our data sets. Only 4.03% and 3.60% of movie showings in the first and second data sets had more than 90% utilization of their seating capacities.[9] In fact, the mean utilization per movie showings is just 26.74% for the first data set and 25.71% for the second. Therefore, handling the factor of capacity-constrained attendance is not a priority concern in our demand models.

Another issue common among other pre-announced time schedule service providers, but less so in multiplex movie theaters, is the price variation across different services offered. Similar to their counterparts in the U.S., our focal multiplex movie theater charges differential prices for showings starting in different time slots (e.g., matinees) and for moviegoers of different ages (e.g., senior discounts), but there is no differentiation of prices across different movie titles. As a result, the price variation is perfectly correlated with the outside option's time of day variation. Therefore, the price effect will be completely absorbed by the time of day effects in our demand models and there is no need to include any price variables. Note that this

[9] Utilization is defined as the ratio of total admissions (i.e. sum of free and paid admission) to the total number of seats available.

is unique to the movie exhibitors. Demand models for other pre-announced schedule service providers typically must capture the pricing decision variables separately.

As our three models are essentially share models, we need to transform the admissions totals to shares. The transformation takes two steps. First, we group movie showings by their starting hours. Each hour is defined as a choice occasion. Note that around 1% of movie showings face another showing of the same title within one choice occasion (hourly period). Assuming multiple showings of the same titles are equivalent to perfectly correlated choice alternatives within a choice occasion, we therefore combine the admissions of the multiple showings into the admission of one choice alternative. After this combination, there are 5,856 "unique" movie showings in the first data set and 20,970 "unique" movie screenings in the second data set. Second, we obtain the shares of individual showings by dividing the admissions by the total number of potential moviegoers. We set the total potential market size equal to the average monthly admissions in our first sample, 73,962. The rationale is as follows. According to 2003 market statistics released by the Motion Picture Association in the U.S., 25% of the U.S. population aged 12 and over (accounting for 78% of total admissions) are frequent moviegoers, who visit theaters at least once per month. If we assume that the moviegoer behaviors in Amsterdam, where our focal movie theater is located, are similar to those in the U.S., the monthly total attendance in our multiplex theater should be a rough approximation for the "maximum" number of potential customers at any snapshot of time. To put this assumption into perspective, note that the population of Amsterdam over age ten in 2001 was 652,270, which is roughly nine times 73,962.[10] Also note that there were movie showings in our two data sets with zero admissions, resulting in zero shares. As our three models require taking logarithm of the

[10] Different total market sizes have been tried and the estimation results are qualitatively similar.

shares, we replace these zeros with 1/73,962, which is equivalent to only one admission for the showing.[11]

Before discussing the estimation results of the three models, we first examine some patterns in our two data sets. Table-1a, 1b and 1c show the admission per showing in the first data set by different hours of day, different days of week, and by different weeks. Table-2a-2g show the admission per showing by different hours of Sundays, Mondays, etc. As discussed in the model development section, these tables suggest the following patterns in the first data set:

1) 9pm appears to be the best time slot in which to start a movie.
2) Saturday and Sunday appear to be the best and second best days of the week.
3) The weeks covering spring vacation (Mar 3-Mar 11, 2001) and Easter weekend (Apr13-16, 2001) appear to attract more people than other weeks.
4) As shown in Table-2a-2g, the time of day pattern (admission per showing increases as showings get closer to 9pm) is quite robust across different days of the week, except Sunday. In particular, Sunday afternoon appears to do better than Sunday evening. We therefore include a Sunday afternoon effect in the three models.

For the calibration part of the second data set, Table-3a, 3b and 3c show the admission figures per showing by different hours of day, different days of week, and by different weeks; and Table-4a-4g show the admission per showing by different hours of Sundays, Mondays, etc. The following observations can be made:

1) Unlike in the first data set, 8pm appears to be the best time slot in which to start a movie. This inconsistency leads to an interesting question: Does the time of day preference shift from 2001 to 2004 or does the confounding between movie qualities and time preferences

[11] We have tried replacing those zeros with other values and obtained similar estimation results.

appear more prevalent in one data set than the other? Our three models should be able to address this question.

2) Saturday and Sunday appear to be equally good.
3) The weeks covering Christmas vacation (Dec 20, 2003-Jan 4, 2004) appear to be the most preferred time to watch movies. On the other hand, some of the weeks covering summer vacation (June 28-Aug 31, 2003) appear to draw the lowest number of admissions. The holiday effects in the second data set are less apparent than those in the first data set.
4) Similar to the first data set, the time of day pattern (admission per showing increases as showings get closer to 8pm) is quite robust across different days of a week, except Sunday, in which the afternoon did as well as the evening. Once again, it suggests that a Sunday afternoon effect is very plausible.

Examining Table-2a-2g or Table-4a-4g, one may wonder if there is any variation in the number of movie choices in each hour across different days, since the numbers of showings in individual hours appear to be relatively constant across different days of the week. For example, Table-2a-2g show that 10pm appears to have the same number of showings on Sundays, Mondays, etc. This is an important concern, as the number of movie choices enters our crowding model as one of the explanatory variables. However, one should note from Table-1c or Table-3c that while the pattern of numbers of showings across different hours is relatively stable across different days of a week, the number of showings varies greatly across different weeks. Figure-1 and 2 show the weekly number of showings across different weeks in the two samples. As we can see, there is non-trivial variation in the number of showings across different weeks, and this weekly variation should help identify the parameters associated with the time of day effect and the crowding effect (i.e. numbers of movie choices in individual choice occasions). In fact, we may get a sense of how the admissions per showings vary with the number of movie choices by examining the Pearson correlation between the admission per showings and the number of movie choices in individual hours. Such a correlation is 0.30 in the first data set and -0.10 in the second data set. While the second data set's correlation is in line with our expectation (more movie choices results in more cannibalization, resulting in lower admissions to each movie), the first data set suggests an opposite effect. This inconsistency further reinforces the need to study discrete choices using structural models like our three models, which control for the three layers of seasonality and the unobserved quality.

Our three models control for unobserved movie quality with a pair of movie-specific parameters. In particular, if we have more than a one-week observation for a movie, we estimate a movie-specific intercept, θ_j, and a movie-specific weekly decay factor, λ_j; otherwise we estimate only θ_j. Note that some movie titles have versions in different languages. For example, *102 Dalmatians* and *102 Dalmatiers* are the same movie, but the first is in English and the second is in Dutch. To capture any subtle differences between these versions, we treat different versions of the same movie title as separate movies. Therefore, the first data set has 48 movie titles. Moreover, in the second data set, 64 movie showings (0.3% of all movie showings) are non-first run movie titles, and each of these movie titles were shown only once. As each of these "classic" movies essentially has only one observation, we cannot estimate the pair of movie-specific parameters. Assuming that these classic movies have by and large the same mean appeal to potential moviegoers, we group these movies as one unique movie title called "classics" and estimate one group-specific intercept, θ. As a result, for the second data set, the calibration part includes 147 movie titles plus a group of classics and the validation part adds three more titles.

Two weather variables are hypothesized to affect the outside option. The first weather variable is the daily average temperature (in degrees Celsius) measured in De Bilt, the weather station closest to Amsterdam. Another weather variable is the daily precipitation duration (in 0.1 hour) measured in De Bilt. Table-5 shows the summary statistics of these two variables in the first and second data sets. Figure-3, 4, 5 and 6 are the plots of these weather variables over the observation windows of the two data sets. Comparing the plots of the two data sets, we can see that the longer duration of the second data set allows more apparent weather trends, daily temperature in particular, to emerge. It suggests that the second data set should give a better sense of how the daily temperature affects the outside option.

5. Estimation Results

We now discuss the estimation results of the three models developed in section 3. For comparison purposes, we also estimate some variants, which adopt Einav's (2003) specifications instead. First, in addition to allowing each movie title to have its own weekly decay rate, λ_j, we follow Einav to develop some model variants by restricting all movie titles to have the same weekly decay rate. Second, as Einav captures the time of year seasonality using weekly parameters, we also estimate model variants that use weekly parameters instead of holiday parameters. Furthermore, to further explore the approaches used to distinguish cannibalization and market expansion effects, we also estimate a hybrid model that combines the features of both the nested logit and crowding models. Specifically, similar to the derivation of the crowding model, we assume that the choice probabilities of the hybrid model also depend on the degree of crowding in the unobserved product space, while the unobserved utility components are assumed to be distributed as in the nested logit model. Using Berry's (1994) inversion method, we can express the exploratory hybrid model as[12]:

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[12] We set $R_{jhd}/R_{0hd} = (J_{hd})^{\gamma}$ as this is equal to the original specification used in Ackerberg and Rysman's (2002) additive model.

$$\ln(s_{jhd}) - \ln(s_{0hd}) = \tau_{hd} + \delta_{jd} + \sigma\cdot\gamma\cdot\ln(J_{hd}) + \sigma\cdot\ln(s_{jhd|C_{hd}}) + \xi_{jhd} \qquad (34)$$

As discussed in the previous section, we estimate different versions of the base and crowding models, (15) and (31), by OLS. This estimation approach is similar to the least square estimation method put forward by Theil (1969). For the nested logit model as well as the hybrid model, as the conditional share, $s_{jhd|C_{hd}}$, is an endogenous variable to $\ln(s_{jhd}) - \ln(s_{0hd})$, we cannot estimate (24) or (34) by OLS. Instead, we introduce instrumental variables for $s_{jhd|C_{hd}}$ and estimate (24) and (34) using the two-stage least square method. For movie j's observation in the choice occasion of hour h on date d, the instruments for $s_{jhd|C_{hd}}$ are the percentages of competing movies in the choice occasion, $\frac{I_{\{k\}}}{\sum_{\forall l \neq j \in C_{hd}} I_{\{l\}}}$, $\forall k \neq j$. These instruments are chosen because the percentages of competing movies in a choice occasion are certainly correlated with the conditional shares, $s_{jhd|C_{hd}}$, but should be independent of ξ_{jhd}, the error specific to movie j. In fact, the instruments are statistically significant in the first stage of the two-stage least square estimation of (24) and (34), and Hausman's tests of exogeneity show that the conditional shares, $s_{jhd|C_{hd}}$, are endogenous with these instruments.[13]

Note that when estimating the models, we set some parameters at zero for identification purposes. In the first data set, we chose *Cast Away* starting in the hour of 9pm on Saturday as the base case and set the corresponding parameters, $\theta_{Cast\ Away}$, ω_{SA}, and β_{9pm} equal to zero. The intercept in (15), (31), (24) and (34) therefore becomes $\omega_0 + \omega_{SA} + \beta_{9pm} + \theta_{Cast\ Away}$ and the estimates for other time of day, day of week and movie-specific parameters are indeed the differences between the corresponding weekdays, hours or titles and the base case. Similarly, in

[13] We conducted a simpler version of Hausman's test of exogeneity (Greene 2002, p.385): we first regress $s_{jhd|C_{hd}}$ on all the exogenous variables including the instruments and then regress $\ln(s_{jhd}) - \ln(s_{0hd})$ on its explanatory variables (except the instruments) as well as the residual of the first regression. Testing if the coefficient of the residual is significantly different from zero is equivalent to testing if $s_{jhd|C_{hd}}$ is exogenous. In all of our nested logit and hybrid models, the coefficients of the residuals are statistically different from zero.

the second data set, we set the parameters associated with Classics starting in the hour of 8pm on Saturday as the base case.

Table-6 reports the estimation results of six models using our first data set, January 4 – April 18, 2001. These six models are variants of the base and crowding models, which capture the time of year effect by holiday effects:

M11: The base model without the Sunday afternoon effect

M12: The base model with the Sunday afternoon effect, which is exactly (15)

M13: The crowding model with R_{jhd}/R_{0hd} specified as (33a), $(J_{hd})^{\gamma_a}$

M14: The crowding model with R_{jhd}/R_{0hd} specified as (33b), $\exp(\gamma_{b1} \cdot J_{hd})$

M15: The crowding model with R_{jhd}/R_{0hd} specified as (33b), $\exp(\gamma_{c1} \cdot J_{hd} + \gamma_{c2} \cdot J_{hd}^2)$

M16: The base model restricting the weekly decay rate to be the same for all movie titles, which is one of the features in Einav's (2003) specification

We also test another feature of Eianv's specification, which is the capture of the time of year effect by weekly parameters. We replace the holiday effects in the above six models with the weekly parameters. Table-7 reports the estimation of these models using the first data set:

M21: The base model without the Sunday afternoon effect

M22: The base model with the Sunday afternoon effect

M23: The crowding model with R_{jhd}/R_{0hd} specified as (33a), $(J_{hd})^{\gamma_a}$

M24: The crowding model with R_{jhd}/R_{0hd} specified as (33b), $\exp(\gamma_{b1} \cdot J_{hd})$

M25: The crowding model with R_{jhd}/R_{0hd} specified as (33b), $\exp(\gamma_{c1} \cdot J_{hd} + \gamma_{c2} \cdot J_{hd}^2)$

M26: The base model with a movie-average weekly decay rate

Finally, Table-8 reports the estimation results of the nested logit (*IV1*) and hybrid models (*IV2*) using the first data set. There are a total of 14 models for the first data set. Similarly, the same

14 models are estimated with the calibration part of the second data set, May29, 2003 – May 26, 2004. Table-9 and Table-10 report the estimation results of *M11-M16* and *M21-M26*, respectively. Table-11 contains the results of *IV1* and *IV2*.

Movie-specific Weekly Decay Rate

For brevity of presentation, we do not report the estimation results of the movie-specific parameters. However, almost all of λ_j estimates are negative if they are significantly different from zero. Across *M11-M16*, *IV1* and *IV2*, there is only one movie in the first data set and around ten movies in the second that have statistically positive weekly decay rates. However, all these movies are either left-censored (the opening weeks are before the left end of our observation window, May 29, 2003) or family-oriented movies (e.g., *Cheaper by the Dozen* or *Pokemon 4*). As the targeted moviegoers for the family-oriented movies probably did not have an urgent need to see the movies during the release weeks, the corresponding decay rates may behave differently. We therefore argue that *M11-M16*, *IV1* and *IV2* all give reasonable λ_j estimates. On the other hand, as we will discuss later, the weekly effects in *M21-M26* are likely to be confounded with the weekly decay rates, and therefore some estimated λ_j have unexplainable positive signs.

Time of Day effects: Good Movie or Nothing Better to Do?

Our earlier examination of the raw data pattern suggests that the first and second data sets have two different best hours to start a movie. In particular, Table-1 shows that 9pm is the best hour from January to April 2001, while Table-3 shows that 8pm is the best hour from May 2003 to May 2004. However, these observations have not accounted for the possible uneven movie quality across different hours. It is not clear whether 9pm is an hour with many good movies or if 9pm has a low utility of outside option. As shown in Table-6-8, all models estimated with the first data set give a very consistent result, namely that 8pm is the most preferred hour for moviegoers to watch movies, a finding which is contradictory to the raw data pattern. In other words, by structurally disentangling the underlying time preference from unobserved varying movie quality, we now know that the high average admission per showing in the hour of 9pm is not due to the lowest outside option utility, but to better movies. Moreover, all structural models also show that the time of day effect increases as showings move towards the evening. On the other hand, consistent with the raw data pattern, all models in the second data set give a consistent result: 8pm is the best time slot and movie-watching becomes more attractive than the outside option as screenings move closer to the evening.

Day of Week Effects

All models in the first and second data sets give a very consistent result: Saturday is the best day of the week to watch movies and Sunday is usually as good as Saturday. This result is consistent with our earlier explanation that the opportunity cost of watching movies on the weekend is lower than that on weekdays.

Sunday Afternoon Effect

Also consistent with our earlier argument, all models in both data sets consistently demonstrate a Sunday afternoon effect. In fact, when we do not have SUNPM in both data sets (i.e. M11), Sunday appears to be statistically stronger than Saturday, which is not in line with the raw data pattern (Table-1a and 3a).

Time of Year Effect

There are two ways to capture the time of year effect, namely the holiday effects and the weekly effects. First, for the holiday effect approach (*M11-M16*), models with the first data set give a very consistent result, namely positive effects from Christmas vacation, spring vacation and Easter weekend. While the spring vacation and Easter weekend results are as expected from the raw data pattern (Table-1c), the Christmas vacation result is an effect uncovered only after controlling for the unobserved movie quality. In the second data set, all holidays are significantly positive, which is once again consistent with the raw data pattern (Table-3c).

For the weekly effect approach (*M21-M26*), models with the first data set give some very unintuitive estimates of the weekly effects, namely a monotonically increasing time trend. The result may be due to the fact that we do not have replication of each week of a year (i.e. we do not observe the same holidays for several years in one continuous data set). Therefore, our weekly binaries are likely to confound somewhat with the weekly variation of unobserved movie quality. In particular, when we compare the estimated λ_j of the holiday effect and weekly effect approaches in the first data set, we observe that the latter tends to be more negative than the former. Together with the increasing time trend associated with the weekly effect, the weekly effect approach may allow the models to have a more flexible pattern of decay, namely an up and down trend within a specific movie's theatrical run.

Similarly, the weekly effects estimated with the second data set also lack face validity. For example, while the raw data pattern indicates that Christmas vacation (Week 30-32) should include the best weeks and the weeks of June 2003 (Week 3-4) should be relatively average weeks, the estimated weekly effects for the former turn out to be smaller than those for the latter.[14] While one may argue that this is the true seasonality, revealed after controlling for unobserved movie quality, there is no obvious way to test this conjecture.

To evaluate another specification made by Einav (2003), we estimate models using a movie-average decay rate, *M16* and *M26*. While the models with holiday effects (*M16*) in both samples give a significantly negative *AGE* effect, the models with weekly effects (*M26*) give an insignificant *AGE* effect in the first data set and a significantly "positive" *AGE* effect in the second data set. As *M26* is essentially Einav's specification with time of day and day of week effects added, it appears that Einav's specification is not appropriate to our data set.[15] One reason may be that our data sets are not long enough to provide replication of individual weeks of a year.

Weather Effects

While daily precipitation duration consistently gives a significant positive effect in both samples, daily temperature is only significant in the second data set. The insignificance of daily temperature in the first data set may be due to our earlier postulation that the temperature pattern in the first data set is not as apparent as that of the second, which essentially covers the whole year of weather variation.

Cannibalization vs. Market Expansion

We now discuss the two approaches used to distinguish between the cannibalization and market expansion effects when a new movie choice is added to a choice occasion. As the weekly effect approach relatively lacks face validity, we focus hereafter on the holiday effect approach

[14] Unlike the first data set, the second data set does not demonstrate a clear monotonic trend in the weekly effect estimates, and there is no apparent pattern in the estimated λ_j.
[15] Of course, to begin with, the specification of constant decay is overly strong and counterintuitive.

(*M13-M15*, *IV1* and *IV2*). The crowding models can be discussed (*M13-M15*) first. For the first data set, the number of movie choices is insignificant in all three specifications of the crowding models, *M13- M15*. For the second data set, while the number of movie choices is insignificant in the log form (*M13*), it has a significant negative sign in the linear form (*M14*). Probably due to increased multicolinearity, when the number of movie choices is in quadratic form (*M15*), only the squared term is significantly negative at the 10% level. As discussed earlier, when $\ln(R_{jhd}/R_{0hd})$ is close to zero, the crowding model is close to a standard logit model, suggesting that a new movie choice added to a choice occasion would substitute toward other movie choices and the outside option equally. Apparently, our first data set is more in line with the IIA implied by a standard logit model. On the other hand, while still relatively close to zero, the significant negative $\ln(R_{jhd}/R_{0hd})$ for some specifications in the second data set suggests that when a new movie choice is added, cannibalization tends to be slightly greater than the magnitude suggested by a standard logit model.

Do the nested logit models suggest a similar pattern? Examining *IV1* of Table-8 and Table-11, we can see that the estimated nesting parameters, σ, are statistically larger than zero in both data sets, but still not very large. As discussed earlier, when σ is close to zero, the nested logit model is similar to a standard logit model. Somewhat in line with the results of the crowding models, the relatively small σ estimates in both data sets suggest that new movie showings would substitute more towards other movie showings than towards the outside option, but the effect is not very large.

Finally, we examine the hybrid models (*IV2* in Table-8 & Table-11). In both data sets, the sign of ln(no. of movie choices) now becomes positive. At first glance, it appears to suggest a "variety effect" (new choice alternatives increase the utility of existing choice alternatives), rather than cannibalization. However, we also need to consider σ. In fact, the estimated σ in *IV2* are larger than the estimated σ in the pure nested Logit model *IV1*, suggesting more cannibalization within the movie choice nest in *IV2*. Apparently, the positive coefficient of ln(no. of movie choices) compensates for this larger estimated σ. Figure-7 shows the predicted share of a base case movie showing when the same base case movie continues to be added to the choice occasion. The predictions are made by four models, namely the base model, *M12*; the nested logit, *IV1*; the crowding model, *M13*; and the hybrid model, *IV2*; on the basis of the second data set estimation results. As the base model is a standard logit, which cannot distinguish the cannibalization and market expansion effect, it is not surprising to see that it gives approximately a horizontal straight line. Moreover, as expected, the nested logit and crowding models predict the share of admissions for a movie showing to decrease as more choice alternatives are added. However, it is interesting to note that the hybrid model also has a downward-sloping curve in Figure-7, suggesting that the larger estimated σ dominates the effect of positive coefficient of ln(no. of movie choices). In fact, if we compare the curves of the three non-standard logit models, we can see that, 1) the crowding model's curve is relatively flat; 2) the nested logit has the largest slope, especially moving from one to two showings; and 3) the hybrid model has both of the above features, namely a large slope when the choice set is small and a trend toward relative flatness afterward (essentially overlapping with the crowding model's curve, beyond seven showings). This suggests that the positive coefficient of ln(no. of movie choices) in *IV2* is more likely to increase the flexibility of the model in terms of characterizing the data pattern than to result in a variety effect.

Let us further examine how our four models (*M12*, *IV1*, *M13* and *IV2*) respond to the variation in choice set size. Figure-8 shows individual models' predicted total share of all showings of the base case movie when the choice set size increases. As we can see, all four models predict that the total share of all movie showings will increase as the number of movie showings in an hour increases. As expected, the standard logit (*M12*) predicts a larger market expansion effect than the other three models, which are designed to better distinguish between the cannibalization and market expansion effects. Another observation from Figure-8 is that the market expansion effect predicted by the standard logit does not diminish as fast as that in other models when the choice set size increases. We can see this more clearly from Table-12, which shows the four models' predicted incremental share changes in situations with an additional showing. As we can see, the standard logit model predicts very similar incremental gains in the group share, regardless of choice set size. Moreover, if we compare the models' predicted incremental gains of group shares from one to two showings and those from seven to eight showings, we can see that the incremental gains predicted by the other three models are diminishing at a faster rate than those of the standard logit model. This suggests that the standard logit tends to overestimate the gain resulting from the addition of extra showings, especially when the choice set is already large. On the other hand, we observe a similar pattern when examining the changes in individual shares: the standard logit model does not predict as much diminishment of individual share losses as the other three models when the choice set size increases. If we combine the patterns of both individual shares and group shares, we see the following: 1) the standard logit model predicts that the marginal effect of adding a new movie choice to a choice set is rather insensitive to the total choice set size; and 2) the other three models predict that as a choice set increases, each extra showing will create less impact on the outside option and individual movie choices.

Predictive Performance

Given that the base model has such a good fit to the data (as indicated by the high R^2), there is a limit as to how much model discrimination we can obtain. In fact, when examining the model fitness criteria such as AIC and BIC, it appears that the models are similar in terms of fit. Following the tradition established by Guadagni and Little (1983), we therefore examine how these models perform in the validation part of the second data set, May 27, 2004-June 9, 2004.

In order to obtain the movie-specific parameters for movies that were newly released or had just entered their second week in the validation sample, the models were first estimated in a sample combining both the calibration and validation parts. The new movies' parameters were then inserted into the models calibrated with only the calibration sample to generate predictions for the validation period. Note that the results using such a combined sample are in line with the results of only the calibration sample. Except for the movie-specific parameters of movies new to the validation data set, all models use the estimates reported earlier to generate predictions. For *M21-M26*, because the validation sample approximately covers the same time of year as the first two weeks of the calibration sample, we use the first two of the 52 weekly parameter estimates to generate the predictions.

Table-13 reports the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean squared error (RMSE) of the 14 models in the validation sample. As noted earlier, the models using weekly parameters (*M21-M26*) do not give parameter estimates with high face validity. In fact, as shown in Table-13, they also give very large errors, relative to the models using holiday effects. Therefore, models with weekly parameters are not the preferred approach for capturing time of year seasonality in our context. Among models using holiday effects, the models with the nesting parameter, σ (i.e. nested logit and hybrid), tend to have the lowest error levels, but the results are generally close. This is probably due to the fact that the cannibalization-correction parameters in the crowding model and the nested logit model, γ and σ, are not very different from zero, meaning all these models are largely similar to the base model.

6. Concluding Remark

We have successfully disentangled the time of day and day of week effects from the unobserved movie quality. In particular, simply by examining average admission per showing starting in different hours, we find that our two samples give different answers regarding the best time slot in which to start a movie: 9pm in the first data set vs. 8pm in the second data set. However, once we control for the unobserved movie quality using our models, 8pm is revealed as the best hour in both data sets. More importantly, at least from a substantive viewpoint, the time effects are relatively consistent across the two data sets, although magnitude may vary.

This essay extends Einav's work in three ways. First, our focus is studying two more micro levels of seasonality, time of day and day of week, while shedding light on yearly seasonality. Second, allowing a more flexible weekly decay for the unobserved movie quality improves the seasonality estimates. Third, we begin to examine the issue of choice set variation by comparing two approaches, namely the nested logit and Ackerberg & Rysman's specification. We provide a unifying framework for examining those two approaches, while Ackerberg and Rysman motivated their model in an independent manner. Both approaches suggest that our two data sets should have slightly more cannibalization than those suggested by the standard logit when new movie choices are added to an hour. Although the effects are relatively small in magnitude, they suggest that a standard logit model is insufficient for both data sets. Further research could examine both the absolute and relative importance of expansion and cannibalization at other time intervals. In fact, one should note that this pattern may be limited by our assumption of choice occasion. For clean demonstration of our models, the present study simply defines a choice occasion as one hour. Further research efforts should relax this assumption. For example, by defining a choice occasion as a day or a week, the demand models need to be extended to capture another aspect of moviegoers' behaviors, for example substitution between a screening of *Star Wars Episode III* on Monday at 7pm and a showing on Saturday at 11am.

The demand models developed in this essay can be used by managers. They can serve as a diagnostic tool to help managers understand the time preferences of potential moviegoers. Further research can take one further step by modifying the demand models for decision optimization purposes like MMSS. In particular, new models should address the challenges of generating movie-specific parameters for forthcoming or new movies. Moreover, further research should go beyond data sets from multiplex movie theaters. For other pre-announced schedule service providers such as airlines, retail price is another important decision variable, which further complicates the issue of time preferences and unobserved service quality.

7. References:

Ackerberg, Daniel A. and Marc Rysman (2002), "Unobserved Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects," working paper, UCLA

Ben-Akiva, Moshe and Steven R. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press

Berry, Steven T. (1994), "Estimating discrete-choice models of product differentiation," *RAND Journal of Economics*, 25(2), 242-262

Cardell, N. Scott (1997), "Variance Components Structures for the Extreme-value and Logistic Distributions with Application to Models of Heterogeneity," *Econometric Theory*, 13, 185-213

Cooper, Lee G. and Masao Nakanishi (1988), *Market-Share Analysis: Evaluating Competitive Marketing Effectiveness*, Kluwer Academic Publishers

Einav, Liran (2003), "Gross Seasonality and Underlying Seasonality: Evidence from the U.S. Motion Picture Industry," working paper, Stanford University

Eliashberg, Jehoshua, Sanjeev Swami, Charles B. Weinberg and Berend Wierenga (2001), "Implementing and Evaluating SilverScreener: A Marketing Management Support System for Movie Exhibitors," *Interfaces*, 31(3), S108-S127

Givon, Moshe, and Dan Horsky (1990), "Untangling the Effects of Purchase Reinforcement and Advertising Carryover," *Marketing Science*, 9(2), 171-188

Greene, William H., (2000) *Econometric Analysis*, 4th ed., Prentice Hall

Guadagni, Peter M. and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2(3), 203-238

Hanssens, Dominique M., Leonard J. Parsons and Randall L. Schultz (2003), *Market Response Models: Econometric and Time Series Analysis*, 2nd ed., Kluwer Academic Publishers

McFadden, Daniel (1978), "Modelling the Choice of Residential Location," in *Spatial Interaction Theory and Residential Location*, A. Karlquist et al., eds, North Holland

McGill, Jeffrey I. and Garrett J. Van Ryzin (1999), "Revenue Management: Research Overview and Prospects," *Transportation Science*, 33(2), 233-256

Theil, Henri (1969), "A Multinomial Extension of the Linear Logit Model," *International Economic Review*, 10, 251-259

Pierce, David A., Michael R. Grupe, and William P. Cleveland (1984), "Seasonal Adjustment of the Weekly Monetary Aggregates: A Model-based Approach," *Journal of Business and Economic Statistics*, 2(3), 260-270

Sawhney, Mohanbir S., and Jehoshua Eliashberg (1996), "A parsimonious model for forecasting gross box-office revenues of motion pictures," *Marketing Science*, 15(2), 113-131

Swami, Sanjeev, Jehoshua Eliashberg and Charles B. Weinberg (1999), "SilverScreener: A Modeling Approach to Movie Screens Management," *Marketing Science*, 18(3), 352-372

Train, Kenneth (2001), *Discrete Choice Methods with Simulation*, Cambridge University Press

Wierenga, Berend and Gerrit van Bruggen (2000), *Marketing Management Support Systems*, Kluwer Academic Publishers

Table-1a: Admission per Showing in Different Time of Day (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	311	3301	10.61
12pm	619	7560	12.21
1pm	465	10788	23.20
2pm	512	19048	37.20
3pm	534	20810	38.97
4pm	472	18618	39.44
5pm	261	5952	22.80
6pm	763	50469	66.15
7pm	518	31313	60.45
8pm	252	18232	72.35
9pm	820	93045	113.47
10pm	329	16857	51.24

Table-1b: Admission per Showing in Different Days of Week (Jan 4, 2001 – Apr 18, 2001)

Showings available on:	No. of Showings	Total Admission	Admission per Showing
SUN	840	56893	67.73
MON	835	27968	33.49
TUE	831	26776	32.22
WED	841	32428	38.56
THU	835	39652	47.49
FRI	834	48146	57.73
SAT	840	64130	76.35

Table-1c: Admission per Showing in Different Weeks (Jan 4, 2001 – Apr 18, 2001)

Showings available between:		No. of Showings	Total Admission	Admission per Showing
4-Jan-01	10-Jan-01	410	18463	45.03
11-Jan-01	17-Jan-01	378	17716	46.87
18-Jan-01	24-Jan-01	388	18814	48.49
25-Jan-01	31-Jan-01	385	17426	45.26
1-Feb-01	7-Feb-01	378	15915	42.10
8-Feb-01	14-Feb-01	393	19641	49.98
15-Feb-01	21-Feb-01	400	19986	49.97
22-Feb-01	28-Feb-01	397	25258	63.62
1-Mar-01	7-Mar-01	392	26613	67.89
8-Mar-01	14-Mar-01	376	21433	57.00
15-Mar-01	21-Mar-01	399	17531	43.94
22-Mar-01	28-Mar-01	397	19310	48.64
29-Mar-01	4-Apr-01	395	18887	47.82
5-Apr-01	11-Apr-01	385	17042	44.26
12-Apr-01	18-Apr-01	383	21958	57.33

Table-2a: Admission per Showing in Different Time of Day on Sunday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	46	716	15.57
12pm	89	1678	18.85
1pm	65	2740	42.15
2pm	73	5782	79.21
3pm	78	6605	84.68
4pm	68	6180	90.88
5pm	38	1774	46.68
6pm	109	11340	104.04
7pm	74	5106	69.00
8pm	36	2313	64.25
9pm	117	11337	96.90
10pm	47	1322	28.13

Table-2b: Admission per Showing in Different Time of Day on Monday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	43	357	8.30
12pm	89	836	9.39
1pm	67	1118	16.69
2pm	74	1924	26.00
3pm	75	2011	26.81
4pm	67	1566	23.37
5pm	37	536	14.49
6pm	109	5140	47.16
7pm	74	3019	40.80
8pm	36	1733	48.14
9pm	117	8568	73.23
10pm	47	1160	24.68

Table-2c: Admission per Showing in Different Time of Day on Tuesday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	43	451	10.49
12pm	87	794	9.13
1pm	68	999	14.69
2pm	72	1418	19.69
3pm	75	1572	20.96
4pm	67	1161	17.33
5pm	36	382	10.61
6pm	109	4651	42.67
7pm	74	3189	43.09
8pm	36	2063	57.31
9pm	117	8869	75.80
10pm	47	1227	26.11

Table-2d: Admission per Showing in Different Time of Day on Wednesday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	46	459	9.98
12pm	90	819	9.10
1pm	63	1242	19.71
2pm	74	2412	32.59
3pm	78	2036	26.10
4pm	68	1577	23.19
5pm	38	539	14.18
6pm	109	5482	50.29
7pm	74	3715	50.20
8pm	36	2318	64.39
9pm	118	10359	87.79
10pm	47	1470	31.28

Table-2e: Admission per Showing in Different Time of Day on Thursday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	44	461	10.48
12pm	87	1138	13.08
1pm	69	1650	23.91
2pm	73	2107	28.86
3pm	75	2268	30.24
4pm	67	1901	28.37
5pm	37	559	15.11
6pm	109	6489	59.53
7pm	74	4697	63.47
8pm	36	2648	73.56
9pm	117	13400	114.53
10pm	47	2334	49.66

Table-2f: Admission per Showing in Different Time of Day on Friday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	43	548	12.74
12pm	88	1291	14.67
1pm	68	1674	24.62
2pm	73	2523	34.56
3pm	75	2606	34.75
4pm	67	2231	33.30
5pm	37	707	19.11
6pm	109	6601	60.56
7pm	74	4727	63.88
8pm	36	3093	85.92
9pm	117	18388	157.16
10pm	47	3757	79.94

Table-2g: Admission per Showing in Different Time of Day on Saturday (Jan 4, 2001 – Apr 18, 2001)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
11am	46	309	6.72
12pm	89	1004	11.28
1pm	65	1365	21.00
2pm	73	2882	39.48
3pm	78	3712	47.59
4pm	68	4002	58.85
5pm	38	1455	38.29
6pm	109	10766	98.77
7pm	74	6860	92.70
8pm	36	4064	112.89
9pm	117	22124	189.09
10pm	47	5587	118.87

Table-3a: Admission per Showing in Different Time of Day (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	738	9848	13.34
11am	914	15439	16.89
12pm	1944	34006	17.49
1pm	1943	52755	27.15
2pm	1677	58236	34.73
3pm	1883	77134	40.96
4pm	1899	67949	35.78
5pm	1309	46004	35.14
6pm	2203	103620	47.04
7pm	1751	102590	58.59
8pm	1133	108128	95.44
9pm	2715	223844	82.45
10pm	861	43976	51.08

Table-3b: Admission per Showing in Different Days of Week (May 29, 2003 – May 26, 2004)

Showings available on:	No. of Showings	Total Admission	Admission per Showing
SUN	3240	184928	57.08
MON	2903	93878	32.34
TUE	2887	102036	35.34
WED	2888	98381	34.07
THU	2904	124309	42.81
FRI	2891	148851	51.49
SAT	3257	191146	58.69

Table-3c: Admission per Showing in Different Weeks (May 29, 2003 – May 26, 2004)

Showings available between:		No. of Showings	Total Admission	Admission per Showing
29-May-03	4-Jun-03	410	9995	24.38
5-Jun-03	11-Jun-03	400	13804	34.51
12-Jun-03	18-Jun-03	404	11506	28.48
19-Jun-03	25-Jun-03	410	16028	39.09
26-Jun-03	2-Jul-03	424	15699	37.03
3-Jul-03	9-Jul-03	460	17119	37.22
10-Jul-03	16-Jul-03	434	10983	25.31
17-Jul-03	23-Jul-03	463	14036	30.32
24-Jul-03	30-Jul-03	440	18123	41.19
31-Jul-03	6-Aug-03	469	11052	23.57
7-Aug-03	13-Aug-03	465	11348	24.40
14-Aug-03	20-Aug-03	437	17193	39.34
21-Aug-03	27-Aug-03	406	22668	55.83
28-Aug-03	3-Sep-03	415	18661	44.97
4-Sep-03	10-Sep-03	394	14330	36.37
11-Sep-03	17-Sep-03	396	17625	44.51
18-Sep-03	24-Sep-03	402	12969	32.26
25-Sep-03	1-Oct-03	399	15471	38.77
2-Oct-03	8-Oct-03	390	14904	38.22
9-Oct-03	15-Oct-03	453	25577	56.46
16-Oct-03	22-Oct-03	430	18937	44.04
23-Oct-03	29-Oct-03	394	14674	37.24
30-Oct-03	5-Nov-03	415	13870	33.42
6-Nov-03	12-Nov-03	373	18687	50.10
13-Nov-03	19-Nov-03	379	13624	35.95
20-Nov-03	26-Nov-03	332	25638	77.22
27-Nov-03	3-Dec-03	369	26497	71.81
4-Dec-03	10-Dec-03	356	20964	58.89
11-Dec-03	17-Dec-03	364	19256	52.90
18-Dec-03	24-Dec-03	400	33496	83.74
25-Dec-03	31-Dec-03	398	36273	91.14
1-Jan-04	7-Jan-04	364	26801	73.63
8-Jan-04	14-Jan-04	340	21422	63.01
15-Jan-04	21-Jan-04	351	19921	56.75
22-Jan-04	28-Jan-04	361	18691	51.78
29-Jan-04	4-Feb-04	385	22957	59.63
5-Feb-04	11-Feb-04	370	21031	56.84
12-Feb-04	18-Feb-04	388	19893	51.27
19-Feb-04	25-Feb-04	391	19258	49.25
26-Feb-04	3-Mar-04	389	23663	60.83
4-Mar-04	10-Mar-04	403	19451	48.27
11-Mar-04	17-Mar-04	388	14765	38.05
18-Mar-04	24-Mar-04	410	15031	36.66

Table-3c (continued): Admission per Showing in Different Weeks (May 29, 2003 – May 26, 2004)

Showings available between:		No. of Showings	Total Admission	Admission per Showing
25-Mar-04	31-Mar-04	409	14587	35.67
1-Apr-04	7-Apr-04	405	16802	41.49
8-Apr-04	14-Apr-04	428	18654	43.58
15-Apr-04	21-Apr-04	419	11517	27.49
22-Apr-04	28-Apr-04	412	13762	33.40
29-Apr-04	5-May-04	430	19201	44.65
6-May-04	12-May-04	448	20265	45.23
13-May-04	19-May-04	387	16391	42.35
20-May-04	26-May-04	411	18459	44.91

Table-4a: Admission per Showing in Different Time of Day on Sunday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	216	4267	19.75
11am	269	7215	26.82
12pm	269	7984	29.68
1pm	279	11968	42.90
2pm	244	14854	60.88
3pm	267	21944	82.19
4pm	273	20189	73.95
5pm	191	12939	67.74
6pm	311	22124	71.14
7pm	251	17716	70.58
8pm	165	14529	88.05
9pm	382	24578	64.34
10pm	123	4621	37.57

Table-4b: Admission per Showing in Different Time of Day on Monday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	65	750	11.54
11am	76	855	11.25
12pm	285	3819	13.40
1pm	274	5653	20.63
2pm	237	5572	23.51
3pm	271	7152	26.39
4pm	271	6106	22.53
5pm	185	3850	20.81
6pm	318	10695	33.63
7pm	249	11160	44.82
8pm	132	10695	81.02
9pm	420	23761	56.57
10pm	120	3810	31.75

Table-4c: Admission per Showing in Different Time of Day on Tuesday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	57	774	13.58
11am	66	982	14.88
12pm	286	4134	14.45
1pm	272	6335	23.29
2pm	240	6619	27.58
3pm	268	7207	26.89
4pm	270	6092	22.56
5pm	187	4222	22.58
6pm	314	11617	37.00
7pm	252	12554	49.82
8pm	168	13920	82.86
9pm	384	23699	61.72
10pm	123	3881	31.55

Table-4d: Admission per Showing in Different Time of Day on Wednesday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	58	748	12.90
11am	63	719	11.41
12pm	287	4157	14.48
1pm	279	6562	23.52
2pm	246	7452	30.29
3pm	271	8162	30.12
4pm	277	5747	20.75
5pm	186	4038	21.71
6pm	315	10725	34.05
7pm	245	11294	46.10
8pm	167	13217	79.14
9pm	377	22284	59.11
10pm	117	3276	28.00

Table-4e: Admission per Showing in Different Time of Day on Thursday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	59	539	9.14
11am	77	987	12.82
12pm	277	4534	16.37
1pm	280	6816	24.34
2pm	237	7199	30.38
3pm	270	8385	31.06
4pm	273	7436	27.24
5pm	186	5319	28.60
6pm	315	13526	42.94
7pm	251	14836	59.11
8pm	169	16175	95.71
9pm	384	32907	85.70
10pm	126	5650	44.84

Table-4f: Admission per Showing in Different Time of Day on Friday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	65	763	11.74
11am	81	1095	13.52
12pm	271	5155	19.02
1pm	279	8327	29.85
2pm	231	7826	33.88
3pm	266	10019	37.67
4pm	265	8765	33.08
5pm	184	5856	31.83
6pm	318	14772	46.45
7pm	252	15515	61.57
8pm	167	18518	110.89
9pm	386	42936	111.23
10pm	126	9304	73.84

Table-4g: Admission per Showing in Different Time of Day on Saturday (May 29, 2003 – May 26, 2004)

Showings starting in the hour of:	No. of Showings	Total Admission	Admission per Showing
10am	218	2007	9.21
11am	282	3586	12.72
12pm	269	4223	15.70
1pm	280	7094	25.34
2pm	242	8714	36.01
3pm	270	14265	52.83
4pm	270	13614	50.42
5pm	190	9780	51.47
6pm	312	20161	64.62
7pm	251	19515	77.75
8pm	165	21074	127.72
9pm	382	53679	140.52
10pm	126	13434	106.62

Table-5: Summary of Weather Variables

Data Set 1: January 4, 2001 – April 18, 2001

	Daily Average Temperature (Degree Celsius)	Daily Precipitation Duration (0.1 Hour)
Mean	4.61	25.84
Standard Deviation	3.75	35.56
Maximum	14.40	174.00
Minimum	– 4.80	00.00

Data Set 2: May 29, 2003 – May 26, 2004

	Daily Average Temperature (Degree Celsius)	Daily Precipitation Duration (0.1 Hour)
Mean	10.57	15.00
Standard Deviation	6.46	29.00
Maximum	25.70	228.00
Minimum	-3.80	0.00

Table-6: Models with Holiday variables (Jan 4, 2001 – Apr 18, 2001)

Model	*M11*		*M12*		*M13*		*M14*		*M15*		*M16*	
R-Square	0.7593		0.7717		0.7717		0.7718		0.7718		0.7407	
Adj R-Sq	0.7547		0.7673		0.7673		0.7673		0.7673		0.7376	
N	5856		5856		5856		5856		5856		5856	
AIC	-0.8853		-0.9379		-0.9375		-0.9377		-0.9375		-0.8242	
BIC	-0.7588		-0.8102		-0.8087		-0.8089		-0.8076		-0.7421	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-5.22	<.0001	-5.17	<.0001	-5.15	<.0001	-5.10	<.0001	-5.16	<.0001	-5.40	<.0001
11am	-2.71	<.0001	-2.71	<.0001	-2.72	<.0001	-2.75	<.0001	-2.76	<.0001	-2.65	<.0001
12pm	-2.13	<.0001	-2.13	<.0001	-2.13	<.0001	-2.15	<.0001	-2.17	<.0001	-2.20	<.0001
1pm	-1.54	<.0001	-1.54	<.0001	-1.54	<.0001	-1.57	<.0001	-1.59	<.0001	-1.52	<.0001
2pm	-1.13	<.0001	-1.24	<.0001	-1.25	<.0001	-1.27	<.0001	-1.29	<.0001	-1.28	<.0001
3pm	-1.03	<.0001	-1.14	<.0001	-1.15	<.0001	-1.17	<.0001	-1.19	<.0001	-1.20	<.0001
4pm	-1.11	<.0001	-1.23	<.0001	-1.24	<.0001	-1.26	<.0001	-1.28	<.0001	-1.24	<.0001
5pm	-1.14	<.0001	-1.26	<.0001	-1.27	<.0001	-1.31	<.0001	-1.31	<.0001	-1.32	<.0001
6pm	-0.54	<.0001	-0.66	<.0001	-0.66	<.0001	-0.66	<.0001	-0.67	<.0001	-0.72	<.0001
7pm	-0.27	<.0001	-0.27	<.0001	-0.28	<.0001	-0.30	<.0001	-0.32	<.0001	-0.31	<.0001
8pm	0.25	<.0001	0.25	<.0001	0.23	0.0008	0.20	0.0070	0.20	0.0071	0.13	0.0128
10pm	-0.36	<.0001	-0.36	<.0001	-0.38	<.0001	-0.41	<.0001	-0.42	<.0001	-0.45	<.0001
SUNPM			0.82	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001
MON	-0.78	<.0001	-0.78	<.0001	-0.78	<.0001	-0.78	<.0001	-0.78	<.0001	-0.79	<.0001
TUE	-0.75	<.0001	-0.75	<.0001	-0.75	<.0001	-0.75	<.0001	-0.75	<.0001	-0.77	<.0001
WED	-0.52	<.0001	-0.52	<.0001	-0.52	<.0001	-0.52	<.0001	-0.52	<.0001	-0.53	<.0001
THU	-0.47	<.0001	-0.47	<.0001	-0.47	<.0001	-0.47	<.0001	-0.47	<.0001	-0.47	<.0001
FRI	-0.25	<.0001	-0.25	<.0001	-0.25	<.0001	-0.25	<.0001	-0.25	<.0001	-0.25	<.0001
SUN	0.07	0.0187	-0.29	<.0001	-0.29	<.0001	-0.29	<.0001	-0.29	<.0001	-0.29	<.0001
Temperature	0.00	0.2378	0.00	0.2385	0.00	0.2378	0.00	0.2368	0.00	0.2321	0.00	0.1143
Precip. Duration	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Easter Weekend	0.57	<.0001	0.57	<.0001	0.57	<.0001	0.57	<.0001	0.57	<.0001	0.41	<.0001
Spring Vacation	0.31	<.0001	0.32	<.0001	0.32	<.0001	0.31	<.0001	0.31	<.0001	0.44	<.0001
Xmas Vacation	0.77	<.0001	0.77	<.0001	0.77	<.0001	0.77	<.0001	0.77	<.0001	0.53	<.0001
ln(N_MOVIE)					-0.01	0.7330						
N_MOVIE							-0.01	0.3113	0.02	0.5268		
N_MOVIE^2									0.00	0.3263		
AGE											-0.17	<.0001

Table-7: Models with Weekly variables (Jan 4, 2001 – Apr 18, 2001)

Model	*M21*		*M22*		*M23*		*M24*		*M25*		*M26*	
R-Square	0.7616		0.7740		0.7740		0.7740		0.7740		0.7398	
Adj R-Sq	0.7566		0.7692		0.7691		0.7691		0.7691		0.7361	
N	5856		5856		5856		5856		5856		5856	
AIC	-0.8910		-0.9440		-0.9436		-0.9437		-0.9434		-0.8168	
BIC	-0.7520		-0.8038		-0.8023		-0.8024		-0.8010		-0.7222	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-4.23	<.0001	-4.16	<.0001	-4.15	<.0001	-4.11	<.0001	-4.16	<.0001	-5.00	<.0001
11am	-2.70	<.0001	-2.69	<.0001	-2.70	<.0001	-2.73	<.0001	-2.73	<.0001	-2.65	<.0001
12pm	-2.11	<.0001	-2.11	<.0001	-2.11	<.0001	-2.12	<.0001	-2.13	<.0001	-2.20	<.0001
1pm	-1.54	<.0001	-1.54	<.0001	-1.55	<.0001	-1.57	<.0001	-1.58	<.0001	-1.51	<.0001
2pm	-1.10	<.0001	-1.21	<.0001	-1.22	<.0001	-1.23	<.0001	-1.25	<.0001	-1.28	<.0001
3pm	-1.01	<.0001	-1.13	<.0001	-1.13	<.0001	-1.15	<.0001	-1.17	<.0001	-1.20	<.0001
4pm	-1.11	<.0001	-1.23	<.0001	-1.23	<.0001	-1.25	<.0001	-1.26	<.0001	-1.23	<.0001
5pm	-1.10	<.0001	-1.22	<.0001	-1.23	<.0001	-1.26	<.0001	-1.26	<.0001	-1.32	<.0001
6pm	-0.55	<.0001	-0.67	<.0001	-0.67	<.0001	-0.67	<.0001	-0.68	<.0001	-0.72	<.0001
7pm	-0.23	<.0001	-0.23	<.0001	-0.24	<.0001	-0.25	<.0001	-0.27	<.0001	-0.31	<.0001
8pm	0.23	<.0001	0.23	<.0001	0.22	0.0013	0.19	0.0079	0.19	0.0080	0.12	0.0188
10pm	-0.31	<.0001	-0.31	<.0001	-0.32	<.0001	-0.34	<.0001	-0.35	<.0001	-0.45	<.0001
SUNPM			0.82	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001
MON	-0.87	<.0001	-0.87	<.0001	-0.87	<.0001	-0.87	<.0001	-0.87	<.0001	-0.88	<.0001
TUE	-0.86	<.0001	-0.86	<.0001	-0.86	<.0001	-0.86	<.0001	-0.86	<.0001	-0.87	<.0001
WED	-0.64	<.0001	-0.64	<.0001	-0.64	<.0001	-0.64	<.0001	-0.64	<.0001	-0.64	<.0001
THU	-0.54	<.0001	-0.54	<.0001	-0.54	<.0001	-0.54	<.0001	-0.54	<.0001	-0.54	<.0001
FRI	-0.28	<.0001	-0.28	<.0001	-0.28	<.0001	-0.28	<.0001	-0.28	<.0001	-0.29	<.0001
SUN	0.05	0.0818	-0.30	<.0001	-0.30	<.0001	-0.30	<.0001	-0.30	<.0001	-0.30	<.0001
Temperature	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Precip. Duration	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Week 1	-1.31	0.3846	-1.34	0.3608	-1.34	0.3616	-1.33	0.3668	-1.31	0.3715	-0.76	0.6250
Week 2	-1.26	0.2655	-1.28	0.2443	-1.28	0.2448	-1.27	0.2482	-1.26	0.2515	-0.74	0.5229
Week 3	-0.86	0.2565	-0.87	0.2346	-0.87	0.2352	-0.87	0.2385	-0.86	0.2417	-0.50	0.5167
Week 4	-0.25	0.5085	-0.26	0.4823	-0.26	0.4831	-0.26	0.4869	-0.26	0.4888	-0.10	0.8030
Week 6	0.45	0.2415	0.45	0.2205	0.45	0.2208	0.45	0.2251	0.44	0.2330	0.28	0.4811
Week 7	1.04	0.1695	1.06	0.1516	1.06	0.1518	1.05	0.1546	1.04	0.1600	0.67	0.3910
Week 8	1.76	0.1197	1.78	0.1053	1.78	0.1054	1.77	0.1074	1.76	0.1110	1.04	0.3674
Week 9	2.51	0.0956	2.55	0.0828	2.54	0.0829	2.53	0.0846	2.51	0.0875	1.48	0.3375
Week 10	2.82	0.1351	2.86	0.1194	2.86	0.1196	2.84	0.1220	2.81	0.1257	1.31	0.4958
Week 11	3.51	0.1205	3.56	0.1057	3.56	0.1059	3.54	0.1077	3.52	0.1104	1.47	0.5254
Week 12	4.28	0.1046	4.34	0.0911	4.34	0.0913	4.32	0.0929	4.29	0.0954	1.62	0.5485
Week 13	5.05	0.0945	5.11	0.0819	5.11	0.0820	5.09	0.0834	5.05	0.0856	1.77	0.5664

Table-7 (Continued): Models with Weekly variables (Jan 4, 2001 – Apr 18, 2001)

Model	*M21*		*M22*		*M23*		*M24*		*M25*		*M26*	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Week 14	6.03	0.0761	6.10	0.0651	6.10	0.0653	6.07	0.0666	6.03	0.0685	2.12	0.5413
Week 15	7.26	0.0547	7.34	0.0459	7.34	0.0460	7.31	0.0470	7.26	0.0484	2.65	0.4932
ln(N_MOVIE)					-0.01	0.8877						
N_MOVIE							-0.01	0.4943	0.01	0.6606		
N_MOVIE2									0.00	0.4997		
AGE											-0.42	0.2823

Table-8: Nested Logit Models with Holiday variables (Jan 4, 2001 – Apr 18, 2001)

Model	*IV1*		*IV2*	
R-Square	0.7969		0.8061	
Adj R-Sq	0.7930		0.8023	
N	5856		5856	
AIC	-1.0859		-1.1429	
BIC	-0.9571		-1.0130	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-5.05	<.0001	-5.31	<.0001
11am	-2.80	<.0001	-2.69	<.0001
12pm	-2.18	<.0001	-2.16	<.0001
1pm	-1.61	<.0001	-1.55	<.0001
2pm	-1.31	<.0001	-1.27	<.0001
3pm	-1.21	<.0001	-1.17	<.0001
4pm	-1.30	<.0001	-1.24	<.0001
5pm	-1.44	<.0001	-1.34	<.0001
6pm	-0.66	<.0001	-0.65	<.0001
7pm	-0.36	<.0001	-0.32	<.0001
8pm	0.06	0.3936	0.16	0.0112
10pm	-0.52	<.0001	-0.43	<.0001
SUNPM	0.82	<.0001	0.82	<.0001
MON	-0.77	<.0001	-0.77	<.0001
TUE	-0.74	<.0001	-0.74	<.0001
WED	-0.51	<.0001	-0.51	<.0001
THU	-0.46	<.0001	-0.45	<.0001
FRI	-0.25	<.0001	-0.25	<.0001
SUN	-0.28	<.0001	-0.28	<.0001
Temperature	0.00	0.1039	0.00	0.0735
Precip. Duration	0.00	<.0001	0.00	<.0001
Easter Weekend	0.56	<.0001	0.55	<.0001
Spring Vacation	0.32	<.0001	0.33	<.0001
Xmas Vacation	0.76	<.0001	0.74	<.0001
σ	0.11	<.0001	0.15	<.0001
ln(N_MOVIE)[16]			0.16	0.0029

[16] The parameter is γ, which is obtained from estimates of $\sigma\cdot\gamma$ and σ by the Delta method

Table-9: Models with Holiday variables (May 29, 2003 – May 26, 2004)

Model	*M11*		*M12*		*M13*		*M14*		*M15*		*M16*	
R-Square	0.6560		0.6617		0.6618		0.6618		0.6619		0.6151	
Adj R-Sq	0.6508		0.6566		0.6566		0.6567		0.6567		0.6119	
N	20970		20970		20970		20970		20970		20970	
AIC	-0.7515		-0.7681		-0.7681		-0.7682		-0.7683		-0.6520	
BIC	-0.6328		-0.6491		-0.6487		-0.6488		-0.6485		-0.5846	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-7.01	<.0001	-7.00	<.0001	-6.97	<.0001	-6.97	<.0001	-7.03	<.0001	-4.86	<.0001
10am	-2.29	<.0001	-2.26	<.0001	-2.25	<.0001	-2.25	<.0001	-2.26	<.0001	-2.12	<.0001
11am	-1.95	<.0001	-1.92	<.0001	-1.91	<.0001	-1.90	<.0001	-1.91	<.0001	-1.88	<.0001
12pm	-1.82	<.0001	-1.83	<.0001	-1.81	<.0001	-1.81	<.0001	-1.82	<.0001	-1.78	<.0001
1pm	-1.27	<.0001	-1.27	<.0001	-1.26	<.0001	-1.25	<.0001	-1.26	<.0001	-1.22	<.0001
2pm	-0.97	<.0001	-1.04	<.0001	-1.03	<.0001	-1.03	<.0001	-1.04	<.0001	-1.01	<.0001
3pm	-0.99	<.0001	-1.06	<.0001	-1.04	<.0001	-1.04	<.0001	-1.05	<.0001	-1.01	<.0001
4pm	-1.09	<.0001	-1.16	<.0001	-1.15	<.0001	-1.14	<.0001	-1.15	<.0001	-1.13	<.0001
5pm	-0.97	<.0001	-1.04	<.0001	-1.04	<.0001	-1.04	<.0001	-1.04	<.0001	-1.02	<.0001
6pm	-0.65	<.0001	-0.72	<.0001	-0.70	<.0001	-0.69	<.0001	-0.70	<.0001	-0.69	<.0001
7pm	-0.26	<.0001	-0.26	<.0001	-0.25	<.0001	-0.25	<.0001	-0.26	<.0001	-0.27	<.0001
9pm	-0.10	<.0001	-0.10	<.0001	-0.08	0.0122	-0.07	0.0420	-0.06	0.0620	-0.08	0.0053
10pm	-0.45	<.0001	-0.45	<.0001	-0.45	<.0001	-0.45	<.0001	-0.44	<.0001	-0.47	<.0001
SUNPM			0.49	<.0001	0.50	<.0001	0.50	<.0001	0.50	<.0001	0.49	<.0001
MON	-0.62	<.0001	-0.62	<.0001	-0.61	<.0001	-0.61	<.0001	-0.61	<.0001	-0.63	<.0001
TUE	-0.52	<.0001	-0.51	<.0001	-0.51	<.0001	-0.51	<.0001	-0.51	<.0001	-0.53	<.0001
WED	-0.50	<.0001	-0.49	<.0001	-0.49	<.0001	-0.49	<.0001	-0.49	<.0001	-0.49	<.0001
THU	-0.34	<.0001	-0.34	<.0001	-0.34	<.0001	-0.34	<.0001	-0.34	<.0001	-0.34	<.0001
FRI	-0.17	<.0001	-0.16	<.0001	-0.16	<.0001	-0.16	<.0001	-0.16	<.0001	-0.18	<.0001
SUN	0.15	<.0001	-0.05	0.0230	-0.05	0.0218	-0.05	0.0211	-0.05	0.0207	-0.04	0.0659
Temperature	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Precip. Duration	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Ascension Day	0.79	<.0001	0.78	<.0001	0.78	<.0001	0.78	<.0001	0.78	<.0001	0.64	<.0001
Whit Day	0.79	<.0001	0.78	<.0001	0.78	<.0001	0.78	<.0001	0.79	<.0001	0.68	<.0001
Easter Weekend	0.52	<.0001	0.51	<.0001	0.51	<.0001	0.51	<.0001	0.51	<.0001	0.48	<.0001
Summer Vacat.	0.19	<.0001	0.19	<.0001	0.19	<.0001	0.19	<.0001	0.19	<.0001	0.17	<.0001
Fall Vacation	0.65	<.0001	0.64	<.0001	0.64	<.0001	0.64	<.0001	0.64	<.0001	0.66	<.0001
Xmas Vacation	0.49	<.0001	0.49	<.0001	0.49	<.0001	0.49	<.0001	0.48	<.0001	0.57	<.0001
Spring Vacation	0.59	<.0001	0.59	<.0001	0.59	<.0001	0.59	<.0001	0.59	<.0001	0.61	<.0001
May Vacation	0.38	<.0001	0.37	<.0001	0.37	<.0001	0.37	<.0001	0.38	<.0001	0.33	<.0001
ln(N_MOVIE)					-0.03	0.1259						
N_MOVIE							-0.01	0.0403	0.02	0.2096		
N_MOVIE^2									0.00	0.0724		
AGE											-0.08	<.0001

Table-10: Models with Weekly variables (May 29, 2003 – May 26, 2004)

Model	*M21*		*M22*		*M23*		*M24*		*M25*		*M26*	
R-Square	0.6617		0.6676		0.6677		0.6677		0.6678		0.6215	
Adj R-Sq	0.6559		0.6619		0.6620		0.6620		0.6620		0.6175	
N	20970		20970		20970		20970		20970		20970	
AIC	-0.7640		-0.7816		-0.7818		-0.7819		-0.7818		-0.6646	
BIC	-0.6290		-0.6463		-0.6461		-0.6461		-0.6457		-0.5808	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-7.42	<.0001	-7.43	<.0001	-7.37	<.0001	-7.38	<.0001	-7.41	<.0001	-27.58	<.0001
10am	-2.27	<.0001	-2.24	<.0001	-2.23	<.0001	-2.23	<.0001	-2.23	<.0001	-2.12	<.0001
11am	-1.93	<.0001	-1.89	<.0001	-1.87	<.0001	-1.87	<.0001	-1.87	<.0001	-1.85	<.0001
12pm	-1.85	<.0001	-1.85	<.0001	-1.83	<.0001	-1.83	<.0001	-1.83	<.0001	-1.82	<.0001
1pm	-1.28	<.0001	-1.28	<.0001	-1.25	<.0001	-1.25	<.0001	-1.26	<.0001	-1.23	<.0001
2pm	-0.99	<.0001	-1.07	<.0001	-1.05	<.0001	-1.05	<.0001	-1.05	<.0001	-1.06	<.0001
3pm	-0.99	<.0001	-1.07	<.0001	-1.04	<.0001	-1.04	<.0001	-1.05	<.0001	-1.03	<.0001
4pm	-1.10	<.0001	-1.17	<.0001	-1.15	<.0001	-1.15	<.0001	-1.16	<.0001	-1.16	<.0001
5pm	-0.98	<.0001	-1.06	<.0001	-1.05	<.0001	-1.05	<.0001	-1.05	<.0001	-1.05	<.0001
6pm	-0.65	<.0001	-0.72	<.0001	-0.69	<.0001	-0.68	<.0001	-0.69	<.0001	-0.71	<.0001
7pm	-0.28	<.0001	-0.28	<.0001	-0.25	<.0001	-0.26	<.0001	-0.26	<.0001	-0.31	<.0001
9pm	-0.12	<.0001	-0.12	<.0001	-0.07	0.0166	-0.06	0.0444	-0.06	0.0567	-0.10	0.0001
10pm	-0.45	<.0001	-0.45	<.0001	-0.46	<.0001	-0.46	<.0001	-0.45	<.0001	-0.49	<.0001
SUNPM			0.50	<.0001	0.51	<.0001	0.51	<.0001	0.51	<.0001	0.50	<.0001
MON	-0.63	<.0001	-0.63	<.0001	-0.63	<.0001	-0.63	<.0001	-0.62	<.0001	-0.64	<.0001
TUE	-0.56	<.0001	-0.55	<.0001	-0.55	<.0001	-0.55	<.0001	-0.55	<.0001	-0.57	<.0001
WED	-0.54	<.0001	-0.53	<.0001	-0.53	<.0001	-0.53	<.0001	-0.53	<.0001	-0.54	<.0001
THU	-0.35	<.0001	-0.35	<.0001	-0.35	<.0001	-0.35	<.0001	-0.35	<.0001	-0.36	<.0001
FRI	-0.20	<.0001	-0.19	<.0001	-0.19	<.0001	-0.19	<.0001	-0.19	<.0001	-0.20	<.0001
SUN	0.16	<.0001	-0.04	0.0732	-0.04	0.0678	-0.04	0.0661	-0.04	0.0656	-0.03	0.1457
Temperature	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Precip. Duration	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001	0.00	<.0001
Week 1	1.90	<.0001	1.90	<.0001	1.91	<.0001	1.90	<.0001	1.89	<.0001	23.06	<.0001
Week 2	1.96	<.0001	1.96	<.0001	1.97	<.0001	1.96	<.0001	1.95	<.0001	22.71	<.0001
Week 3	1.59	<.0001	1.58	<.0001	1.59	<.0001	1.58	<.0001	1.57	<.0001	21.94	<.0001
Week 4	1.62	<.0001	1.62	<.0001	1.63	<.0001	1.62	<.0001	1.61	<.0001	21.50	<.0001
Week 5	1.56	<.0001	1.56	<.0001	1.56	<.0001	1.56	<.0001	1.55	<.0001	20.88	<.0001
Week 6	1.24	<.0001	1.24	<.0001	1.24	<.0001	1.23	<.0001	1.22	<.0001	20.00	<.0001
Week 7	0.73	0.0008	0.72	0.0008	0.72	0.0008	0.71	0.0009	0.71	0.0010	18.94	<.0001
Week 8	0.97	<.0001	0.96	<.0001	0.96	<.0001	0.96	<.0001	0.95	<.0001	18.63	<.0001
Week 9	1.36	<.0001	1.36	<.0001	1.36	<.0001	1.36	<.0001	1.35	<.0001	18.42	<.0001
Week 10	0.75	0.0001	0.74	0.0001	0.74	0.0001	0.73	0.0001	0.72	0.0002	17.29	<.0001
Week 11	0.80	<.0001	0.80	<.0001	0.80	<.0001	0.79	<.0001	0.78	<.0001	16.73	<.0001
Week 12	0.79	<.0001	0.79	<.0001	0.79	<.0001	0.79	<.0001	0.78	<.0001	16.18	<.0001

Table-10 (Continued): Models with Weekly variables (May 29, 2003 – May 26, 2004)

Model	*M21*		*M22*		*M23*		*M24*		*M25*		*M26*	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Week 13	1.15	<.0001	1.15	<.0001	1.16	<.0001	1.15	<.0001	1.14	<.0001	15.92	<.0001
Week 14	0.84	<.0001	0.85	<.0001	0.85	<.0001	0.85	<.0001	0.84	<.0001	14.96	<.0001
Week 15	0.52	0.0017	0.52	0.0013	0.52	0.0014	0.51	0.0016	0.51	0.0019	14.04	<.0001
Week 16	0.49	0.0023	0.49	0.0019	0.49	0.0018	0.49	0.0021	0.48	0.0025	13.51	<.0001
Week 17	0.27	0.0797	0.28	0.0709	0.28	0.0687	0.27	0.0767	0.26	0.0875	12.68	<.0001
Week 18	0.38	0.0112	0.38	0.0095	0.39	0.0092	0.38	0.0105	0.37	0.0122	12.16	<.0001
Week 19	0.42	0.0037	0.43	0.0031	0.43	0.0031	0.42	0.0036	0.41	0.0042	11.50	<.0001
Week 20	1.04	<.0001	1.04	<.0001	1.04	<.0001	1.03	<.0001	1.02	<.0001	11.46	<.0001
Week 21	0.80	<.0001	0.80	<.0001	0.81	<.0001	0.80	<.0001	0.79	<.0001	10.49	<.0001
Week 22	0.49	0.0005	0.49	0.0004	0.49	0.0004	0.49	0.0005	0.48	0.0006	9.50	<.0001
Week 23	0.56	<.0001	0.56	<.0001	0.57	<.0001	0.56	<.0001	0.55	<.0001	8.89	<.0001
Week 24	0.60	<.0001	0.60	<.0001	0.60	<.0001	0.59	<.0001	0.59	<.0001	8.31	<.0001
Week 25	0.55	<.0001	0.55	<.0001	0.55	<.0001	0.54	<.0001	0.53	<.0001	7.57	<.0001
Week 26	0.69	<.0001	0.69	<.0001	0.69	<.0001	0.68	<.0001	0.68	<.0001	7.25	<.0001
Week 27	0.34	0.0051	0.35	0.0042	0.35	0.0044	0.34	0.0053	0.33	0.0064	6.46	<.0001
Week 28	0.04	0.7508	0.04	0.7228	0.04	0.7478	0.03	0.7770	0.03	0.8061	5.63	<.0001
Week 29	0.05	0.6478	0.05	0.6209	0.05	0.6306	0.05	0.6545	0.04	0.6797	5.02	<.0001
Week 30	0.34	0.0006	0.33	0.0006	0.33	0.0006	0.33	0.0007	0.32	0.0009	4.84	<.0001
Week 31	0.69	<.0001	0.68	<.0001	0.68	<.0001	0.67	<.0001	0.67	<.0001	4.52	<.0001
Week 32	0.28	0.0008	0.28	0.0008	0.28	0.0009	0.27	0.0010	0.27	0.0012	3.42	<.0001
Week 33	0.17	0.0299	0.17	0.0312	0.16	0.0354	0.16	0.0403	0.15	0.0456	2.67	<.0001
Week 34	0.10	0.1839	0.09	0.1938	0.09	0.2064	0.09	0.2128	0.09	0.2170	1.91	<.0001
Week 35	0.01	0.9075	0.00	0.9528	0.00	0.9793	0.00	0.9936	0.00	0.9956	1.20	<.0001
Week 36	0.32	<.0001	0.31	<.0001	0.31	<.0001	0.31	<.0001	0.31	<.0001	0.88	<.0001
Week 38	-0.01	0.8709	-0.01	0.8478	-0.01	0.8408	-0.01	0.8559	-0.01	0.8739	-0.62	<.0001
Week 39	-0.03	0.6926	-0.03	0.7073	-0.02	0.7342	-0.02	0.7263	-0.02	0.7198	-1.33	<.0001
Week 40	0.53	<.0001	0.53	<.0001	0.53	<.0001	0.53	<.0001	0.53	<.0001	-1.51	<.0001
Week 41	0.34	<.0001	0.33	<.0001	0.34	<.0001	0.34	<.0001	0.34	<.0001	-2.50	<.0001
Week 42	0.25	0.0084	0.26	0.0072	0.26	0.0065	0.26	0.0058	0.27	0.0050	-3.31	<.0001
Week 43	0.13	0.2373	0.13	0.2181	0.13	0.2035	0.14	0.1922	0.14	0.1771	-4.11	<.0001
Week 44	0.07	0.5592	0.07	0.5236	0.08	0.5094	0.08	0.4961	0.08	0.4755	-4.81	<.0001
Week 45	0.14	0.2781	0.15	0.2495	0.15	0.2424	0.15	0.2323	0.16	0.2186	-5.41	<.0001
Week 46	0.43	0.0018	0.44	0.0015	0.44	0.0014	0.44	0.0013	0.45	0.0011	-5.88	<.0001
Week 47	0.04	0.7945	0.05	0.7519	0.05	0.7369	0.05	0.7199	0.06	0.6939	-7.08	<.0001
Week 48	0.26	0.1013	0.27	0.0884	0.28	0.0840	0.28	0.0786	0.29	0.0717	-7.61	<.0001
Week 49	0.87	<.0001	0.87	<.0001	0.88	<.0001	0.88	<.0001	0.89	<.0001	-7.82	<.0001
Week 50	0.92	<.0001	0.93	<.0001	0.93	<.0001	0.93	<.0001	0.94	<.0001	-8.65	<.0001
Week 51	0.78	0.0001	0.79	<.0001	0.79	<.0001	0.79	<.0001	0.80	<.0001	-9.74	<.0001
Week 52	1.50	<.0001	1.50	<.0001	1.50	<.0001	1.50	<.0001	1.51	<.0001	-10.07	<.0001

Table-10 (Continued): Models with Weekly variables (May 29, 2003 – May 26, 2004)

Model	*M21*		*M22*		*M23*		*M24*		*M25*		*M26*	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
ln(N_MOVIE)					-0.05	0.0145						
N_MOVIE							-0.01	0.0064	0.01	0.7607		
N_MOVIE^2									0.00	0.3289		
AGE											0.57	<.0001

Table-11: Nested Logit Models with Holiday variables (May 29, 2003 – May 26, 2004)

Model	*IV1*		*IV2*	
R-Square	0.6866		0.7111	
Adj R-Sq	0.6818		0.7067	
N	20970		20970	
AIC	-0.8808		-0.9966	
BIC	-0.7614		-0.8768	
Variable	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	-6.87	<.0001	-6.91	<.0001
10am	-2.24	<.0001	-2.26	<.0001
11am	-1.88	<.0001	-1.91	<.0001
12pm	-1.78	<.0001	-1.80	<.0001
1pm	-1.23	<.0001	-1.28	<.0001
2pm	-1.02	<.0001	-1.05	<.0001
3pm	-1.01	<.0001	-1.04	<.0001
4pm	-1.13	<.0001	-1.16	<.0001
5pm	-1.04	<.0001	-1.05	<.0001
6pm	-0.66	<.0001	-0.70	<.0001
7pm	-0.24	<.0001	-0.28	<.0001
9pm	-0.03	0.3123	-0.08	0.0041
10pm	-0.48	<.0001	-0.50	<.0001
SUNPM	0.50	<.0001	0.49	<.0001
MON	-0.61	<.0001	-0.61	<.0001
TUE	-0.51	<.0001	-0.51	<.0001
WED	-0.49	<.0001	-0.49	<.0001
THU	-0.33	<.0001	-0.33	<.0001
FRI	-0.16	<.0001	-0.16	<.0001
SUN	-0.05	0.0154	-0.04	0.0132
Temperature	0.00	<.0001	0.00	<.0001
Precip. Duration	0.00	<.0001	0.00	<.0001
Ascension Day	0.76	<.0001	0.75	<.0001
Whit Day	0.78	<.0001	0.77	<.0001
Easter Weekend	0.51	<.0001	0.50	<.0001
Summer Vacat.	0.19	<.0001	0.20	<.0001
Fall Vacation	0.64	<.0001	0.63	<.0001
Xmas Vacation	0.49	<.0001	0.49	<.0001
Spring Vacation	0.58	<.0001	0.57	<.0001
May Vacation	0.37	<.0001	0.37	<.0001
σ	0.09	<.0001	0.18	<.0001
ln(N_MOVIE)			0.15	<.0001

Table-12: Predicted Shares of a Base Case Movie on the basis of Data Set 2

Model	The number of showings change from 1 to 2		The number of showings change from 4 to 5		The number of showings change from 7 to 8	
	Individual Share	Group Share	Individual Share	Group Share	Individual Share	Group Share
Standard Logit Model, *M12*	-0.000001	0.000909	-0.000001	0.000904	-0.000001	0.000900
Nested Logit Model, *IV1*	-0.000063	0.000911	-0.000019	0.000822	-0.000011	0.000782
Crowding Model, *M13*	-0.000020	0.000898	-0.000007	0.000864	-0.000004	0.000847
Hybrid Model, *IV2*	-0.000039	0.000920	-0.000012	0.000862	-0.000007	0.000835

Table-13: Predictive Performance in the validation sample (May 27, 2004 – June 9, 2004)

Model	MAE	MAPE	RMSE
M11	26.99	72.69	52.08
M12	26.13	71.03	49.18
M13	26.14	71.07	49.09
M14	26.12	71.07	49.03
M15	26.06	70.93	48.94
M16	27.87	85.62	49.12
M21	44.02	124.65	79.08
M22	43.51	121.67	76.33
M23	44.19	124.00	77.73
M24	43.89	122.76	77.08
M25	43.06	120.10	75.30
M26	16004.53	46864.23	25247.93
IV1	26.08	70.20	48.69
IV2	26.08	69.21	48.78

Figure-1: Weekly Number of Showings from Jan to April 2001

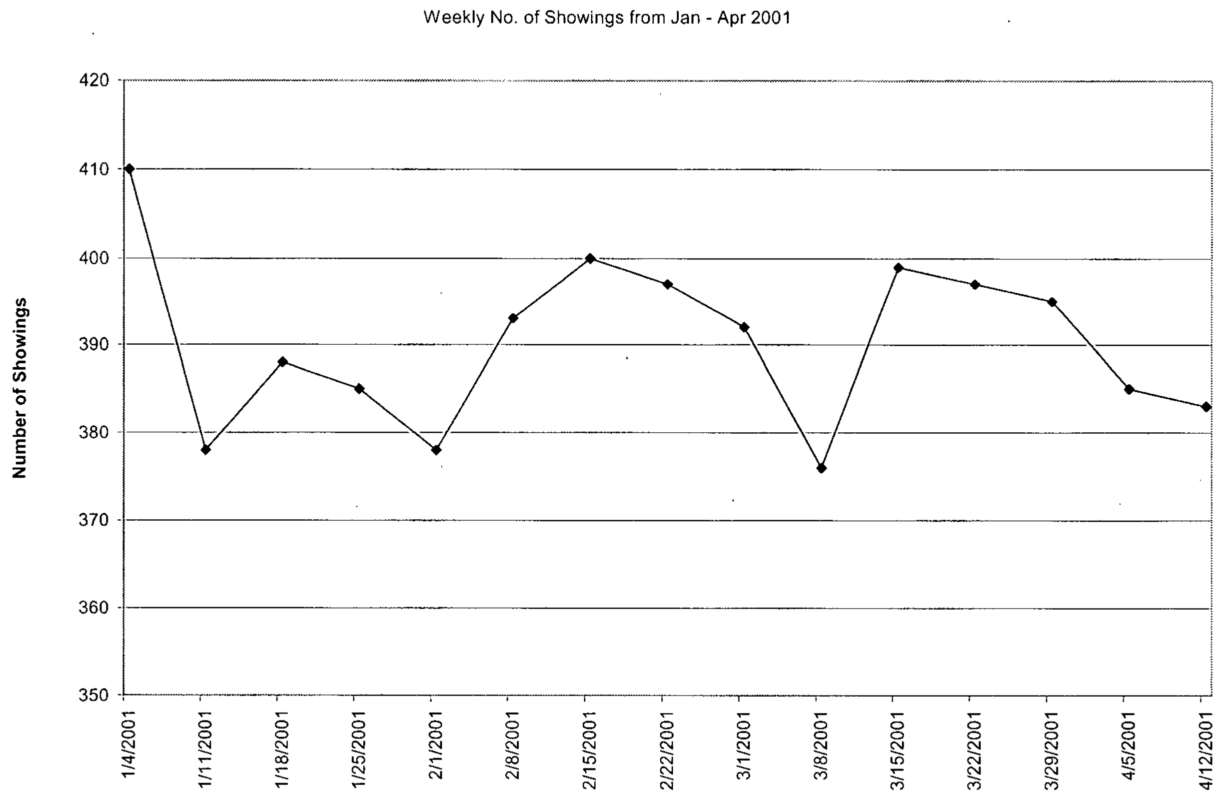


Figure-2: Weekly Number of Showings from May 2003 to May 2004

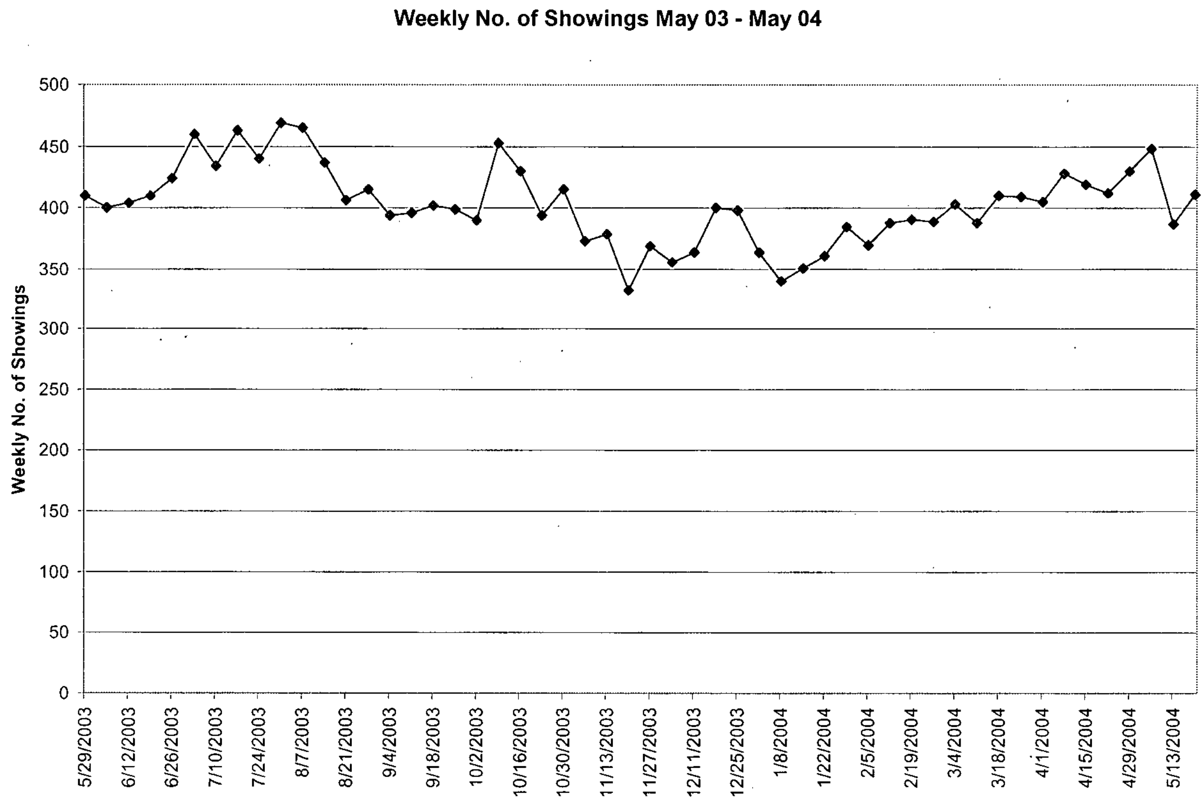


Figure-3: Daily Mean Temperature from January 4 to April 18, 2001

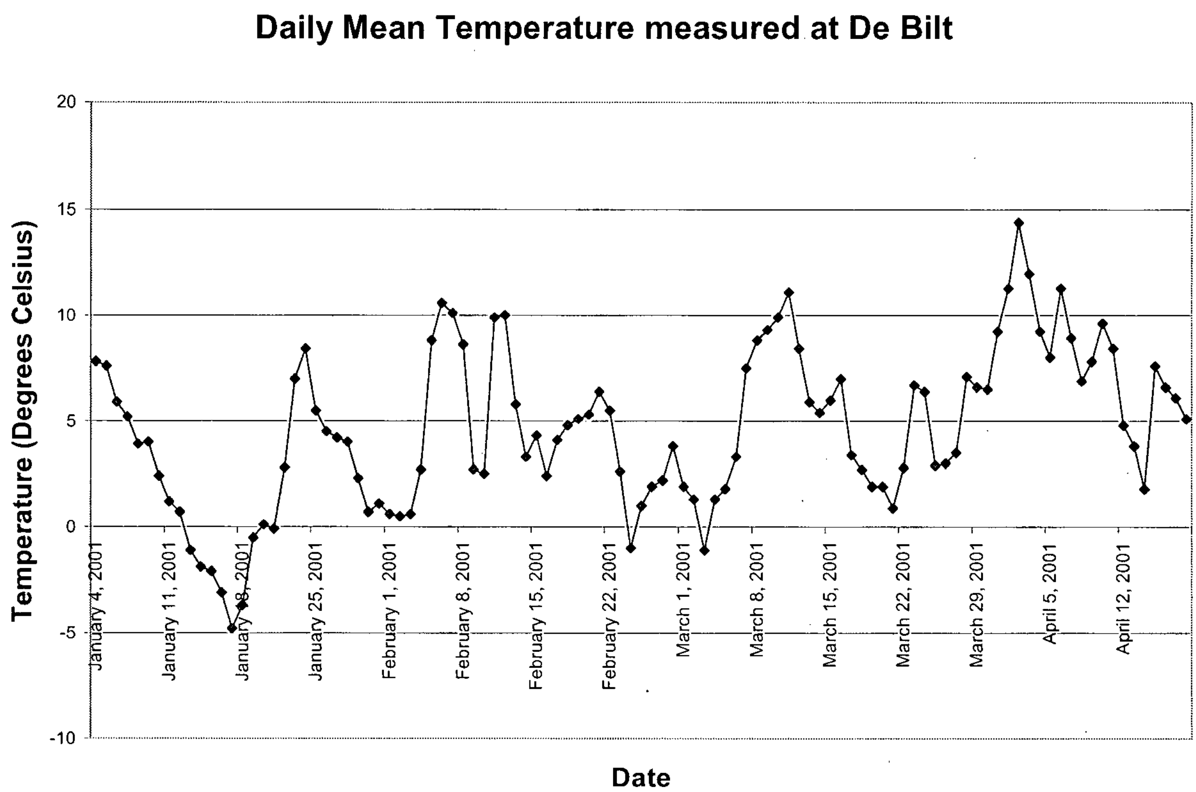


Figure-4: Daily Precipitation Duration from January 4 to April 18, 2001

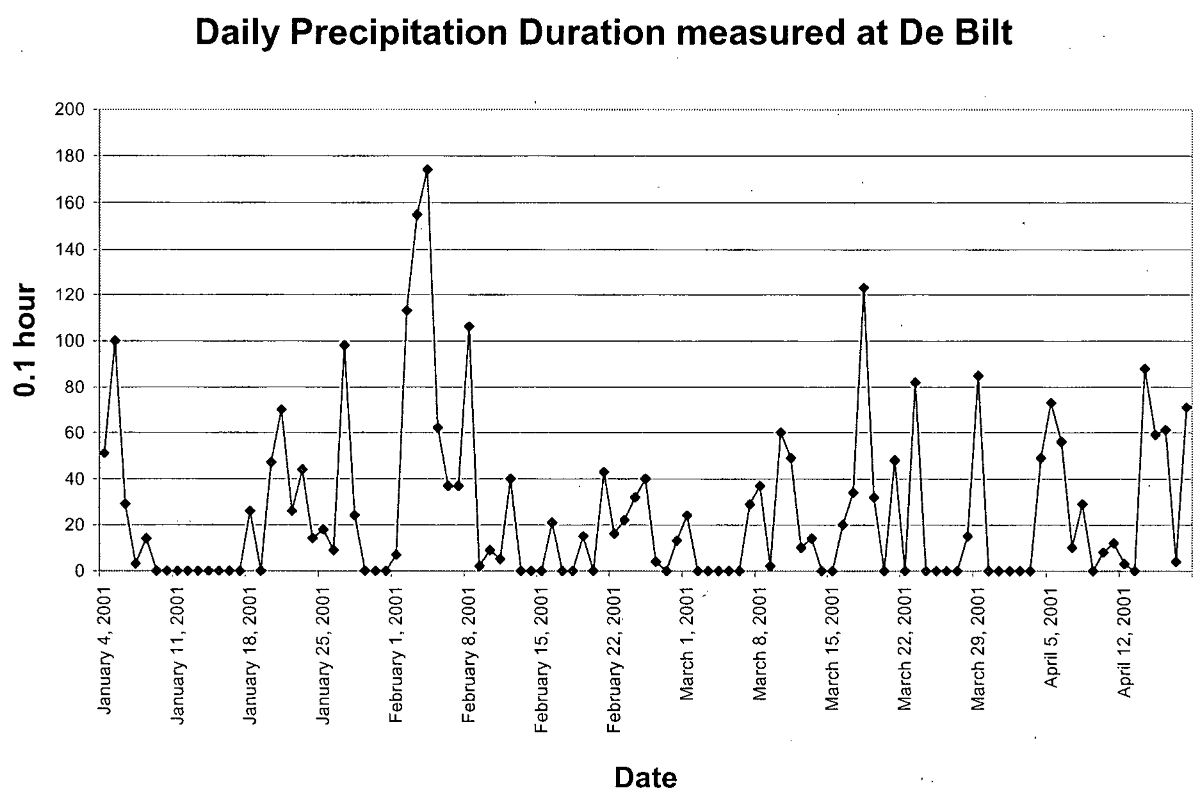


Figure-5: Daily Mean Temperature from May 29, 2003 to May 26, 2004

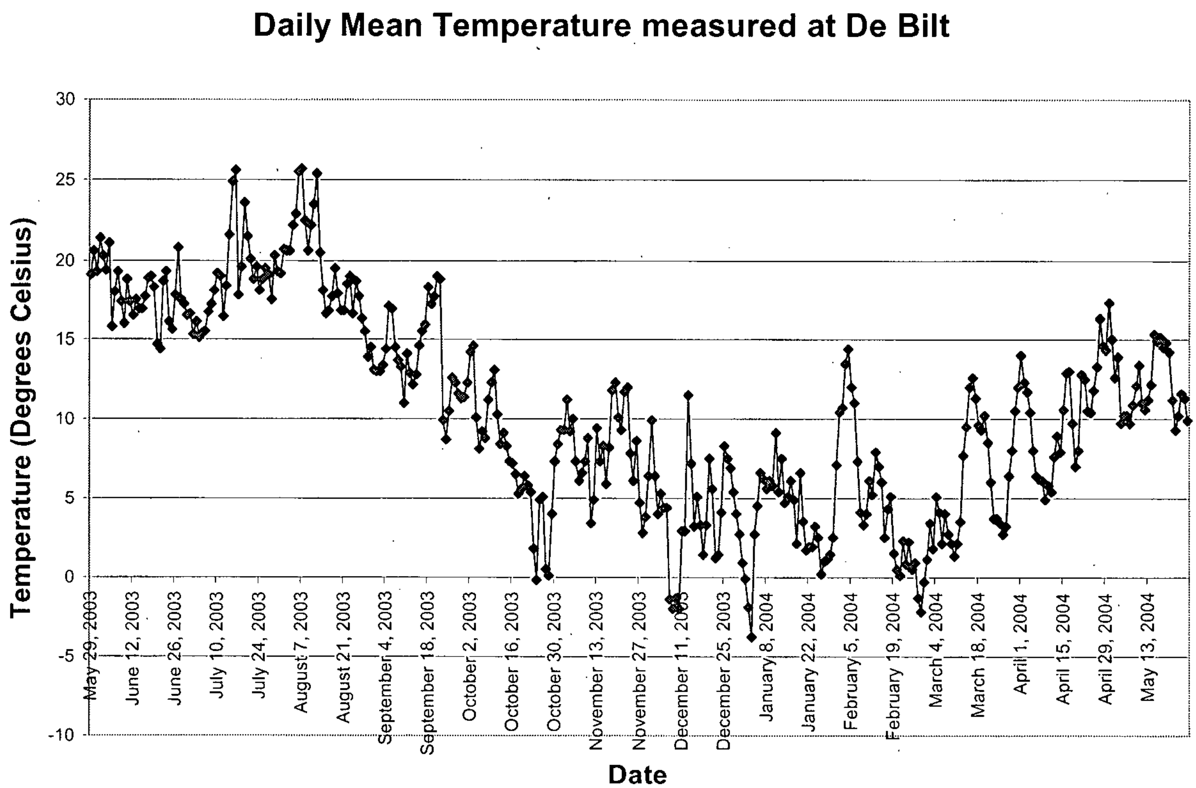


Figure-6: Daily Precipitation Duration from May 29, 2003 to May 26, 2004

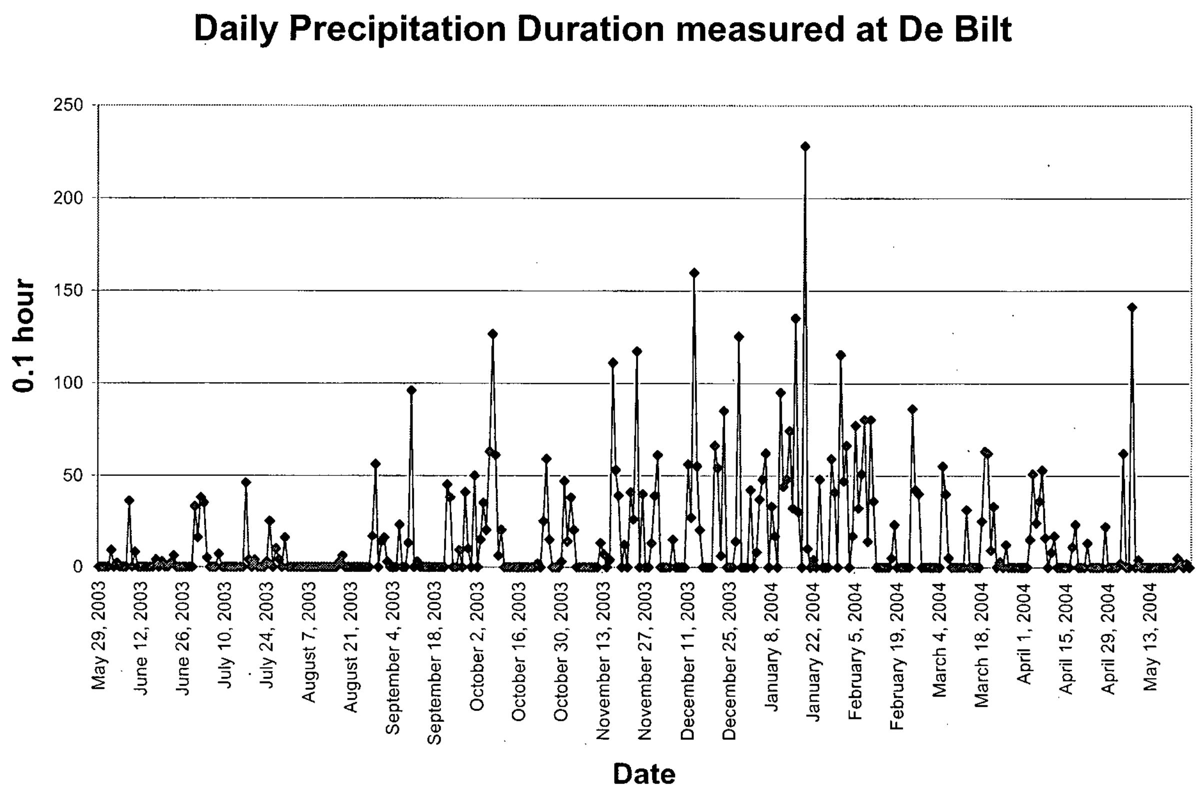


Figure-7: Predicted Share of a Base Case Movie on the basis of Data Set 2: Comparison among Standard Logit (*M12*), Nested Logit (*IV1*), Crowding (*M13*) and Hybrid Models (*IV2*)

(Base Case: a Classic starting in the hour of 8pm on Saturday)

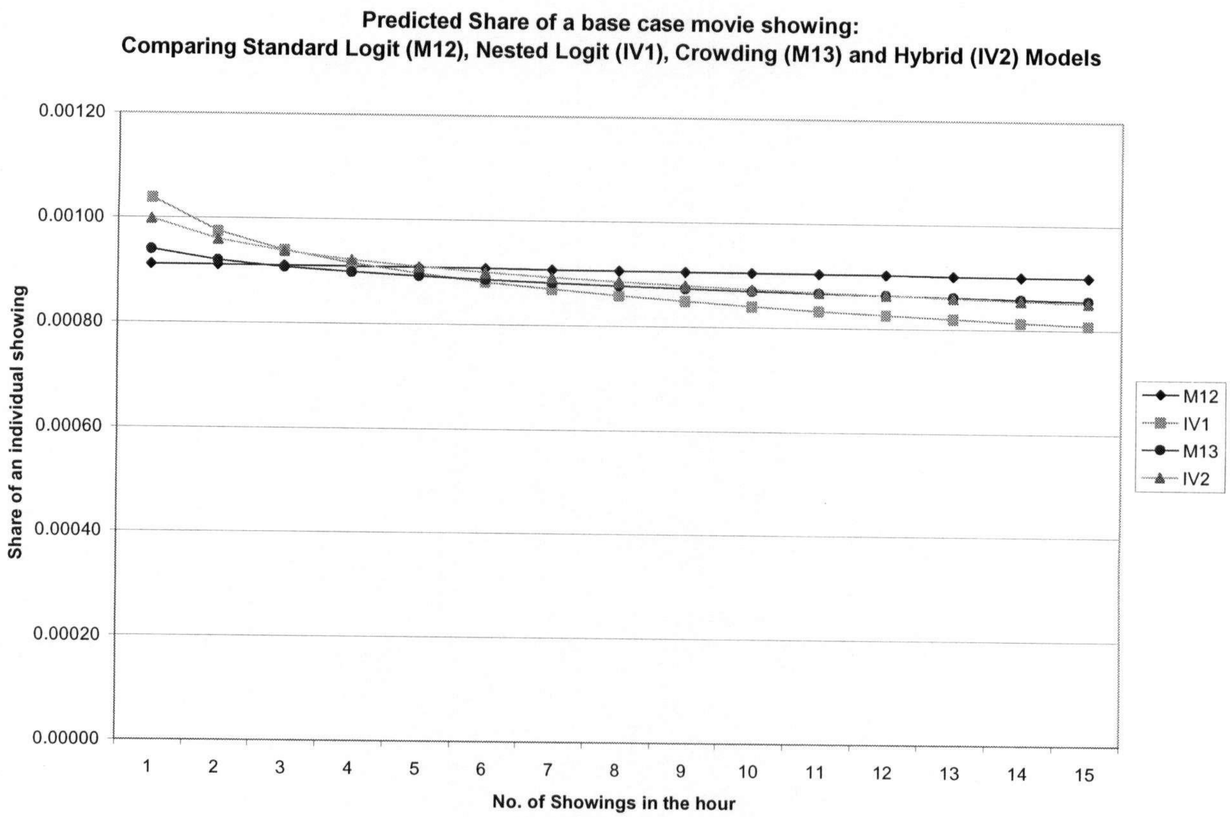
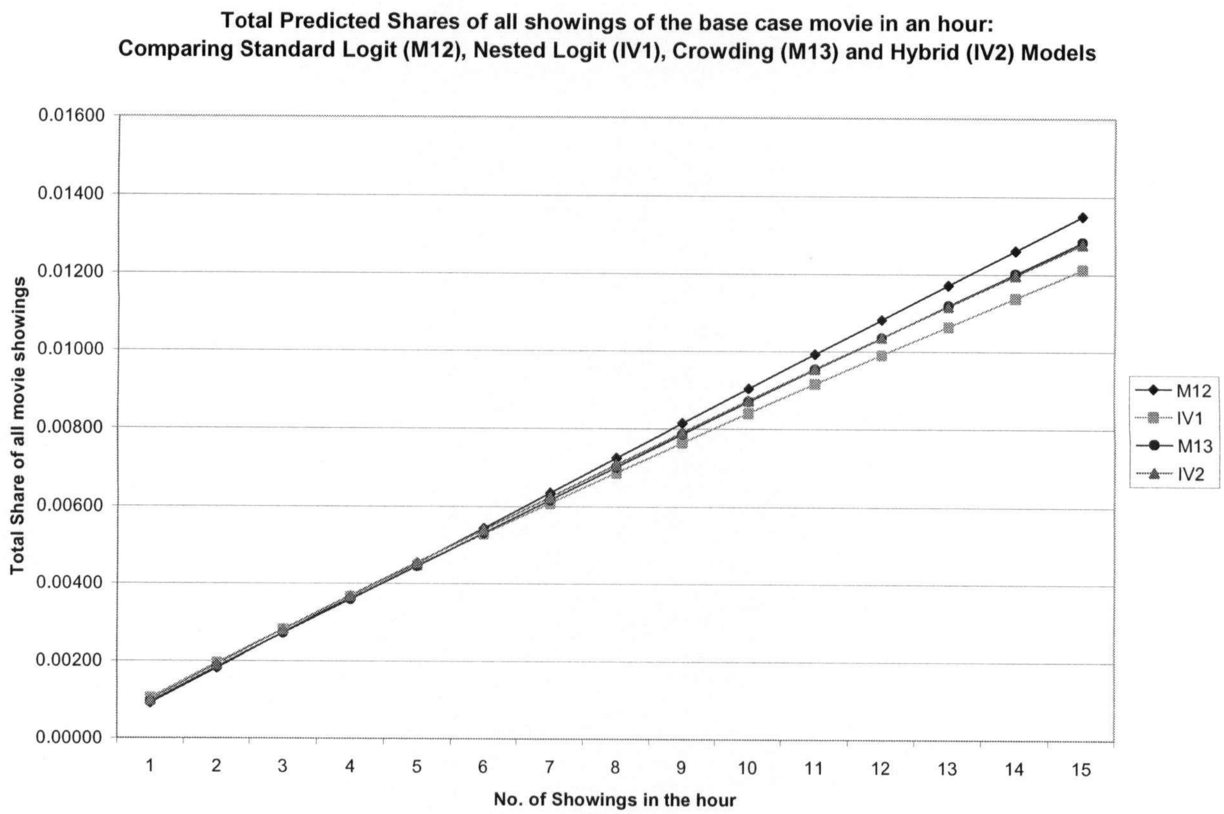


Figure-8: Total Predicted Share of all showings of the Base Case Movie in an hour on the basis of Data Set 2: Comparison among Standard Logit (*M12*), Nested Logit (*IV1*), Crowding (*M13*) and Hybrid Models (*IV2*)



Chapter 5: Conclusion

1. Contributions

There are two levels of contribution intended to be made by each essay of this dissertation. First, using data from the movie industry, we provide substantive findings, which benefit this prominent entertainment industry. Second, the marketing models developed in each essay are intended to advance the concepts and methods used to study more general marketing phenomena. In the following, we present a summary of each essay and discuss its contributions at these two levels.

1.1 Essay 1: Is There a Payoff for Playoffs?

The first essay develops four models to examine the value of Super Bowl TV advertising, and tests the models with a movie sample of 398 wide-release movies from the years 2000-2002. All four estimation models capture a two-path conceptual model for the effects of Super Bowl TV advertising on opening week box office revenues. Specifically, we hypothesize that there are two causal paths associated with such a marketing tactic. First, there is a direct path: Super Bowl TV advertising for a movie directly increases the demand for the movie. Second, there is an indirect path, which consists of two parts. In the first part, Super Bowl TV advertising first encourages more movie exhibitors to screen the movie and thereby increase the availability of the movie to moviegoers. In the second part, the increased product availability in turn increases box office revenues. Although all correspond to this two-path conceptual model, our four estimation models differ in how the non-linearity of the paths and other control variables' effects are captured.

Estimated with a data set integrated from different data sources such as *IMDB.com* and *Entertainment Weekly*, the four models give the following results:

1) Robust to various model specifications, it is found that Super Bowl TV advertising has a positive effect on opening week box office revenue. This effect is present when potential confounding factors like TV campaign start date and total launch TV advertising expenditure are controlled for.

2) Robust to various model specifications, the indirect path of Super Bowl TV advertising is significant. On the other hand, the direct path is significant only in two model specifications. In fact, compared to alternative models, which do not incorporate the mediation of movie exhibitors, the significance of the direct paths in the two-path models is greatly reduced.

3) Except for one model specification, which restricts the marginal effect of three managerial decision variables (Super Bowl TV advertising expenditure, other launch TV advertising expenditure, and product budget) to an increasing pattern, the other three more flexible models show Super Bowl TV advertising to be not as effective as other TV launch advertising efforts when evaluated at the same initial levels.

As mentioned, the essay intends to make contributions at two levels. At the substantive level, we first reconfirmed Yelkur, Tomkovick and Traczyck's (2004) finding that Super Bowl TV advertising increases opening week box office revenues. We used an improved method and better controlling for potential confounding factors. More importantly, we know more about the mechanism of the effect: Super Bowl TV advertising mainly influences opening week box office revenues by increasing the number of movie exhibitors. Finally, while Super Bowl TV advertising creates a non-zero effect on opening week box office revenues, we showed that it is still not as effective as other TV advertising efforts when evaluated at the same initial level. That being said, Super Bowl TV advertising is an attractive tactical alternative when other TV advertising starts generating diminished marginal effects.

At a more conceptual level, the essay contributes to the marketing accountability literature by highlighting the mediating role of downstream channel members when evaluating the effects of marketing tactical actions. Specifically, our results demonstrate the need to evaluate marketing tactics using frameworks incorporating the responses of both downstream channel members and consumers, as in our two-path model.

1.2 Essay 2: Good Movie or Nothing Better to Do?

The second essay develops three demand models for multiplex movie theaters and applies them to two data sets from a multiplex movie theater in Amsterdam. All three models are designed to disentangle moviegoers' three layers of time preference (time of day, day of week, and time of year seasonality) from the unobserved movie quality in the aggregated sales data. While our model specifications are similar to Einav (2003), we depart from his work in three ways: 1) we study seasonality at a more micro level, 2) we relax Einav's restriction that the unobserved quality of all movie titles decays at the same weekly rate, and 3) we address the difficulty of distinguishing cannibalization and market expansion effects when there is choice set variation by relaxing the IIA property in Einav's model. In particular, of the three models, one is a base model maintaining the IIA property. The other two models represent two approaches to relaxing the IIA property, namely the nested logit and Ackerberg and Rysman's (AR 2002) model. While Ackerberg and Rysman motivated their model in an independent manner, we provide a unifying framework to look at the similarities and differences between the two approaches.

Applying the three models to two data sets from the multiplex movie theater in Amsterdam, we obtain the following major findings:

1) Examining the raw patterns of the two data sets, we find that one data set suggests that the most preferred hour to watch movies is 8pm, while the other suggests it is 9pm. This data discrepancy is resolved once we apply the three models to disentangle the time preferences and unobserved movie quality: 8pm is the most preferred hour in both data sets.

2) All three models show that Saturday and Sunday, as well as holidays or school vacations, tend to attract more moviegoers than other days.

3) Both the nested logit and AR models suggest the two data sets have slightly more cannibalization than the magnitude suggested by the standard logit, when new movie choices are added to a choice occasion.

4) While the three models fit the two data sets equally well, nested logit models tend to give a better predictive performance in a validation sample.

Similar to the first essay, the second also makes contributions at two levels. At the substantive level, we found that confounding of unobserved movie quality and underlying time preferences exist in some multiplex movie theaters' gross admission records. This suggests that in some cases, theater managers have a higher tendency to schedule higher quality movies at some time slots than at others. Moreover, we confirmed that the high gross admissions for movie showings on Saturday, Sunday, holidays or school vacations are more due to "nothing better to do" than to "good movies". Finally, we showed that multiplex movie theaters' gross admission records can exhibit more cannibalization than the magnitude suggested by the standard logit, calling for the need to apply nested logit or AR models when analyzing this type of data.

At a methodological level, we showed how the movie-specific parameters θ_j and λ_j can be used to resolve the confounding of unobserved product quality and underlying time preferences in the gross sales data. Note that this method is not limited to multiplex movie theaters, and is applicable to all other service providers that encounter such confounding in their aggregated sales data. More importantly, we demonstrated the similarities and differences of the nested logit and AR congestion models in distinguishing between cannibalization and market expansion effects when there is non-trivial choice set size variation. With our data sets, nested logit models tend to have a slightly better performance.

2. Managerial Implications

The two essays in this dissertation present two types of implications for managerial practices. First, managers should benefit from the substantive findings highlighted above. For example, movie marketers now know the benefit of Super Bowl TV advertising may not be as substantial as that of other TV advertising. This is important if they are considering spending the same amount on either type of advertising. However, they may achieve a larger marginal effect from Super Bowl TV advertising when other TV advertising starts generating diminished marginal returns. Another example is that multiplex movie theater managers now know the raw pattern of their gross sales data sometimes cannot reveal the true time of day seasonality due to the confounding of movie quality and time preferences.

The second type of managerial implication is that the marketing models developed in the two essays could be useful tools for marketing practitioners. We discuss below how our marketing models could be used.

2.1 Essay 1: Is There a Payoff for Playoffs?

In Chapter 3, we demonstrated how a two-path model like our log-quadratic-a model can be used to summarize the direct and indirect effects of such marketing tactics as Super Bowl TV advertising using several elasticity measures. Specifically, from a marketing accountability perspective, marketing practitioners can track these elasticity measures over time to evaluate the response generated by their chosen marketing tactics and whether the marketing tactics are pushing the retailers or directly influencing the end consumers.

More importantly, the four marketing models developed in the first essay can be used directly as market response models to evaluate different tactical alternatives. For example, as shown in the marginal analysis illustration in Chapter 3, marketing practitioners can evaluate the marginal effect of allocating an extra $2.2 million to Super Bowl TV advertising as opposed to allocating it to other TV advertising opportunities by inserting the values corresponding to each tactical alternative into the chosen marketing model.

2.2 Essay 2: Good Movie or Nothing Better to Do?

The demand models developed in the second essay can be used for both diagnosis and decision optimization purposes. For diagnosis, managers of pre-announced time schedule service providers can apply the demand models to their historical sales data and uncover the underlying three layers of seasonality. For decision optimization, the demand models can be used to generate predictions for alternative service schedules. By comparing the predicted sales of different service schedules, marketing practitioners can choose the ones that maximize revenues, subject to operational constraints. However, one should note that while the current version of the demand models is ready to be used to generate predictions for service providers with a rather stable set of services, some modifications are needed for multiplex movie theaters. We will return to this point in the further research section.

3. Further Research

Each of the essays in this dissertation calls for a number of further research directions. We highlight several major ones in this section. In fact, one specific direction from each essay is currently being pursued as an ongoing research project. We will also briefly describe these two ongoing projects.

3.1 Essay 1: Is There a Payoff for Playoffs?

We can extend the movie launch tactic models in several challenging and yet potentially rewarding dimensions:

1) We can explore the dynamic aspect of advertising tactics by going beyond the opening week. As all three parties - movie marketers, movie exhibitors and moviegoers - would adjust their behaviors after observing the movie's box office performance during the previous week, modeling such a feedback mechanism poses some very interesting challenges.

2) We can explore the competition aspect of advertising tactics by considering the strategic behaviors of movie studios. A major challenge here is to define the boundary of a competition set. For example, are movies opening at theaters two weeks apart competing with one another? What about movies opening at theaters four weeks apart?

3) We can explore the weekly allocation of TV advertising expenditures before the movie release. In fact, this direction is currently being pursued in an ongoing project. We briefly discuss the motivation for this extension here.

In examining the detailed allocations for wide-release movies from 2000 to 2002, we recognize a spending pattern not consistent with two mainstay notions in the advertising literature, namely diminishing marginal return to advertising and consumers' forgetting effect. Specifically, the two notions suggest that there are two incentives a movie marketer needs to balance when allocating a movie's launch advertising budget. The diminishing marginal return suggests an incentive to spread the budget evenly across all available weeks leading to the release week, while the consumer forgetting effect implies an opposite incentive to concentrate the entire budget in the release week, when consumers can immediately act upon any aroused interest to watch the movie immediately. By trading off these two incentives, we can show that the optimal launch advertising allocation tactic is to increase the spending levels monotonically in each week as the release date gets closer. However, such a monotonically increasing spending pattern is not the only pattern observed in the movie industry. If we define a monotonically increasing spending pattern as an increasing spending trend with each period having no more than a 20% drop compared to the previous period, around 37% of wide-release movies in 2000-2002 violate this pattern in their last six weeks. To resolve this inconsistency, we are exploring different explanations under the framework involving both responses of movie exhibitors and moviegoers. We believe this project will not only advance our understanding of movie launch tactics, which are cited as an under-researched area by Eliashberg, Elberse, and Leenders (2005), but will also shed light on advertising tactics in a more general context.

3.2 Essay 2: Good Movie or Nothing Better to Do?

The second essay leads to two main future research directions, namely capturing a richer movie-showing substitution pattern and adapting the models to generate predictions for multiplex movie theaters. First, in order to avoid unnecessary complexity when comparing different approaches to relaxing IIA, the second essay assumes each hour is one choice occasion. After establishing the validity of the demand models, we can now explore other choice occasion definitions, e.g., each day is one choice occasion. This extension would allow us to study more complex cannibalization structures among different movie screenings. For example, a screening of *Batman Begins* at 7pm may substitute more toward a showing of *Star Wars: Episode III* at 7pm than toward a showing of *Batman Begins* at 10pm.

Another exciting research direction illuminated by the second essay is adapting the demand models to generate predictions for multiplex movie theaters, which have new movie releases every week. In fact, as an ongoing research project, we are modifying the time of day demand models for use in a marketing management support system (MMSS), called SilverScreener II. The objective of SilverScreener II is to help multiplex movie managers decide how frequently and when a chosen set of movie titles should be shown each week. Similar to other types of MMSS, SilverScreener II consists of two components, namely the demand forecasting model and the decision optimization model. We focus here on the demand forecasting model. A major challenge in adapting the second essay's demand models for the demand forecasting model is assigning movie-specific parameters to movies for which we have not observed any data. An approach which we are currently exploring is to build two additional regression models to predict the movie-specific parameters using some observed characteristics for individual movies. A test of such an approach is now being undertaken with a streamlined version of the estimation models presented here. We believe such research can advance the MMSS literature related to the ways in which demand forecasting and decision optimization models can be integrated on an ongoing basis. It also adds to the forecasting literature on making predictions for new products.

4. References:

Ackerberg, Daniel A. and Marc Rysman (2002), "Unobserved Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects," working paper, UCLA

Einav, Liran (2003), "Gross Seasonality and Underlying Seasonality: Evidence from the U.S. Motion Picture Industry," working paper, Stanford University

Eliashberg, Johoshua, Anita Elberse, and Mark A. A. M. Leenders (2005), "The Motion Picture Industry: Critical Issues in Practice, Current Research and New Research Directions," *Marketing Science*, forthcoming

Yelkur, Rama, Chuck Tomkovick and Patty Traczyk (2004), "Super Bowl Advertising Effectiveness: Hollywood Finds the Games Golden," *Journal of Advertising Research*, March, 143-159