Investigating the Role of Local Market and Exhibitor Characteristics on Box-Office Performance

Sriram Venkataraman[1] Emory University

Pradeep Chintagunta[2] University of Chicago

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[1] Sriram Venkataraman is an assistant professor of marketing at Emory University's Goizueta Business School (Email: svenka2@emory.edu).

[2] Pradeep Chintagunta is the Robert Law Professor of Marketing at the University of Chicago's Graduate School of Business (Email: pradeep.chintaguntachicagogsb.edu).

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Sriram Venkataraman[3] Pradeep Chintagunta[4]
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Abstract

The literature in marketing and economics is quite rich in studies focused on identifying potential drivers of box-office performance of movies. Using national-level cross-sectional data (across movies) and/or panel data (across movies and time), these studies provide valuable insights for distributors and studios alike, i.e. forecasting national-level demand, understanding supply-side and demand-side interdependencies, across-title competition, etc. However, they shed very little light on the actions and potential actions of downstream channel members, i.e. movie theaters and exhibitors.

Driving the overall success of a movie at the national-level, however, is the movie's success at the level of the individual exhibitor (or movie theater). By assembling a rich and unique database of exhibitor-level daily box-office demand, this study identifies factors that drive movie demand at the individual theater-level. Our model and analysis can be of valuable interest to the individual exhibitor, for example, in determining the appropriateness of continuing the screening of the movie for another day or week; studying the impact of local competition on the revenues generated by its screens; and using such analyses as inputs into the decision to manage assortment, increase or decrease the number of screens at an existing location or build a theater at a new location. Understanding the drivers of movie performance at the exhibitor level is also very valuable to upstream channel members, i.e. distributors, so as to identify the most appropriate set of exhibitors to screen their movie. We also examine the implications in forecasting national-level demand if studios ignored disaggregate theater-level data and instead relied on national market-level data while accounting for across-title competition.

Next, we exploit the implications of our model to investigate much-overlooked issues of interest to exhibitors and studios, like a) impact of pricing policy change by exhibitor/exhibitor-chain, b) extending the run of some movies as opposed to others at a given theater location, and c) reallocation of marketing advertising spend between national-level and local-level.

[3] Sriram Venkataraman is an assistant professor of marketing at Emory University's Goizueta Business School (Email: svenka2@emory.edu).

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Clearly, the actions of one member of a channel impact other upstream and downstream channel members. Hence, our analysis, we believe, enhances insights available to several channel members of the motion-picture value chain – i.e. studios, distributors and exhibitors, and complements insights available from extant models and methods.

1. Introduction

A burgeoning literature in marketing and economics has focused on studying the box-office performance of motion pictures. Box-office performance has typically been studied at the level of the movie – country (e.g., U.S.A.) – time period (e.g., week).[5] These studies have shed light on issues such as measuring the impact of box-office drivers (e.g., screens, movie attributes, etc.) on movie performance as well as on studying the roles of factors such as competition, seasonality, word-of-mouth effects, etc. All these models are useful from a descriptive perspective and also a practical perspective to forecast the performance of a movie over time. Thus they provide potentially useful inputs to distributors making decisions on some or all of these box-office drivers.

Driving the overall success of a movie at the aggregate country level, however, is the movie's success at the level of the individual exhibitor (or movie theater). For example, while a majority of the extant studies treat the number of screens as a driver of box-office performance, in reality these screens represent specific locations showing the movie. Thus, while a movie may be playing on 500 screens in a given week, the box-office performance of the movie on one set of 500 screens might be very different from its performance in a different set of 500 screens. Such differences can stem from – a) *cross-sectional differences* or b) *temporal differences*.

Cross-sectional differences <u>*for the same title*</u> arise because of

i) differences in *exhibitor characteristics*: different movies running at the different locations, admission prices charged, the number of screens at each location, proximity to local competitors, seat comfort, concessions, etc.

ii) differences in *market characteristics* (demographics, local-advertising spend, etc.)

iii) interactions between *exhibitor* characteristics and *market characteristics,* and

[5] See for example, Ainslie et al (2005), Einav (2003), Elberse and Eliashberg (2003), Moul (2004), and Neelamegham and Chintagunta (1999) among many others.

iv) movie-related factors (number of competitors showing the same movie, number of new movies introduced at that location, etc.).

Temporal differences *for the same title* arise because of:

i) *time-varying exhibitor characteristics*: temporal variation in competing movies running at the same location, differing times of introduction/exit of a title across locations within the same geographic market, etc.

ii) *time-varying market characteristics:* temporal variation in local- and national-level advertising spends (usually front-loaded), etc.

In order to identify the most appropriate set of exhibitors to screen their movie, a distributor needs to understand the drivers of box-office success at the level of the individual exhibitor. However, aggregate country-level analyses, such as those described previously, do not account for such location-specific effects, since they usually include the total number of screens (regardless of location) as a driver of box-office revenues. Hence these analyses are unsuitable for the identification of locations at which the distributor should be screening (or stop screening) a particular movie.

Understanding the drivers of movie performance at the exhibitor level is also of interest to the individual exhibitor. Within the limits of its contractual obligations vis-à-vis the distributor, the exhibitor is interested in determining the appropriateness of continuing the screening of the movie for another day or week; studying the impact of local competition on the revenues generated by its screens; and using such analyses as inputs into the decision to manage assortment, increase or decrease the number of screens at an existing location or build a theater at a new location. Further, if variables such as price and other theater characteristics are part of the analysis, then the exhibitor can also examine the impact of varying these attributes at its theater on the resulting box-office revenues. While a majority of models and analyses in the marketing literature provide useful insights for movie studios and/or distributors, they shed very little light on the actions and potential actions of movie theaters and exhibitors (for exceptions see the discussion below). Consequently, from the exhibitor's perspective, such studies have little to offer at the micro level of the movie theater.

Our first objective in this paper is to gain a better understanding of the drivers of motion picture box-office performance at the level of the individual exhibitor. To that end, we assemble a unique database of box-office revenues of individual movies over time at the level of the individual exhibitor for the U.S. market. We supplement data with exhibitor-level price and theater characteristics data that are individually surveyed, as well as local market level (i.e., for individual markets within a country) and national as well as local market time series data on advertising expenditures of the individual films.[6] Using these data, we are able to measure the impact on exhibitor-level box-office revenues of movie, market and exhibitor characteristics, as well as potential interactions among these characteristics. While this exercise is largely descriptive, our second objective is to use the outputs of our analysis to address some of the issues (mentioned previously) that cannot be readily addressed with extant models and data. Specifically, we look at the impact of strategic decisions pertinent to exhibitors and distributors, namely:

1. price hike by a focal exhibitor OR exhibitor-chain in a geographic market,
2. reallocation of advertising spend (national to local and local to national)
3. running a movie for an additional day (or week) at a given location

While 1 and 3 provide valuable insights at the individual-exhibitor level or exhibitor-chain level, 2 addresses an issue very pertinent to distributors. We describe the details of these experiments in a later section.

Previous authors have studied issues related to ours. For example, Davis (2005) studies the role of adult admission ticket prices on competition between exhibitors, while Orbach & Einav (2001) study the rationale for the practice of uniform pricing across all titles (at a given location). Elberse and Anand (2005) demonstrate the impact of national-level, pre-release advertising on box-office performance. Building on these studies, our objective here is not to arrive at an optimal pricing/advertising solution given the various complexities involved. Rather, our objective is to see whether the exhibitors (focal and its regional competitors) and distributors can do better under one scenario as opposed to another. Hence, all the above "experiments," we believe, enhance insights available to both the distributor as well as the exhibitor as they complement insights available from extant models and methods.

We also use the model outputs to demonstrate how they can provide potentially useful information for studios as well. In particular, we examine implications for forecasting national-level demand if studios ignored disaggregate theater-level data and instead relied on national market-level data while accounting for across-title competition. At the same time, since our model is formulated at the individual-exhibitor

[6] Thus, while there is cross-sectional variation in the advertising measure across movies and markets, the advertising expenditure in a particular market will be invariant across exhibitors in that market.

level, we can in principle aggregate the output of the model across all exhibitors to provide a forecast of a movie's box-office performance over time at the country level.[7] This latter forecast is precisely what a number of extant models in the literature attempt to do. In some sense then, our framework can be viewed as an alternative to currently available methods for the purpose as well. However, our view on this is that if one only wanted an aggregate prediction, then extant models are more parsimonious as well as easier to implement than our proposed framework. At the same time, their parsimony and simplicity could come at the expense of potential aggregation bias (from aggregating across heterogeneous locations and markets, as has been demonstrated in the scanner-data context by Christen et al. 1997). To that extent, we will view our approach as complementing existing methods for aggregate predictions rather than as a substitute for them.

2. Related literature

As noted previously, our data are quite unique in their scope and coverage within the U.S. market. Nevertheless, there have been a few studies in the economics and marketing literature that have used data at the exhibitor level. In part because of their data limitations, these studies have either exploited cross-sectional variation (theater level and/or title level) or temporal variation, but not both, to understand various aspects of interest to the movie industry. By contrast, we decompose the performance of movies into time-series and cross-sectional components (e.g. accommodate title-specific saturation and time-varying competitive sets).

An early study that focused on the exhibitor was the SilverScreener screen management approach developed by Swami et al. (1999). The focus here was on the individual exhibitor's problem of scheduling the appropriate movie for each screen in the theater, given the demand dynamics of each film as well as new movies becoming available in each week. Using an integer programming approach to determine the allocation of movies to screens over a finite time horizon, the authors show how the theater could enhance its revenues via a better allocation mechanism. While a key input into their exercise is the demand function of the movie, the objective is not to understand the demand drivers per se. Hence Swami et al. focus on a simple demand specification (a two-parameter exponential model) that primarily captures temporal variation in box-office performance of each movie without really focusing on the drivers of interest to us (movie, market and exhibitor characteristics). Additionally, their analysis was carried out for a specific exhibitor in New York City. Another aspect of the study that departs from the current one is

[7] Similar in spirit to store- and market-level data analysis with scanner data.

that since Swami et al. focus on one exhibitor, distributor-related considerations are not part of the analysis.

Closer in spirit to our study are those by Chisholm and Norman (2003) and by Davis (2005). Chisholm and Norman look at motion picture attendance in two markets -- Boston and South Florida -- over the time period from 1996 to 2002. The authors find evidence for both a competitive effect as well as a clustering effect in how the demand for a theater is influenced by the demand at neighboring theaters. In particular, in these markets, the distance to the closest competitor has a positive impact on box-office revenues (the "clustering" effect), whereas the distance to the second (and third) closest competitor has a negative impact on revenues (the "competitive" effect). Different from our focus, the authors are interested in studying only the aggregate performance of a theater (tickets sold per screen per year). As a consequence, aspects specific to a film and a time period of interest (e.g., week) are not investigated. Nevertheless, the analysis is important in that it provides insights into the nature of spatial competition in the movie market.

Like Chisholm and Norman, Davis (2005) is also interested in studying the nature of spatial competition across retail locations (in this case movie theaters). Different from those authors and similar to our study, Davis looks at the demand for a specific movie at a given retail location as the unit of analysis. However, in terms of substantive focus, Davis is interested in examining geographic differentiation of theaters and the extent of their market power. Hence, he does not focus either on potential implications for distributors in terms of determining the appropriate outlets for their movies, or on deriving implications for a given movie at a given exhibitor – issues of central interest to us in this study. Nevertheless, it is the case that we share several common features with Davis both in terms of the data we use as well as the modeling framework. His data cover 607 theaters in 36 markets (covering 39 million people). By contrast, our geographic coverage is as follows: the entire United States spanning 209 A.C. Nielsen's designated market areas (DMA). Further, his time series includes 7 daily observations from June 21 to June 27, 1996. Our data span 16 months of daily data. This enables us to also potentially use our analysis for making time-series forecasts at the individual-theater level over time. Another issue that differentiates our analysis is that we control for the effects of local advertising and national advertising (pre and post-release of the movie) on box-office revenues. As Moul (2006) points out, ignoring the impact of advertising in models of box-office performance could influence the estimated effects of other variables included in the model specification.

The remainder of this paper is organized as follows. In the next section, we describe the data in some detail. Since an important premise of the paper is that differences across exhibitors and local geographic markets play a role in explaining box-office performance, we decompose the variation in box-office performance of the movies in our data over time into (1) *across-movie variation* (title-specific fixed effects); (2) *over-time variation* (time-since national release is days); (3) *across-local-market variation* (market-specific fixed effects); and (4) *across-exhibitor variation* (exhibitor chain-specific fixed effects)

We find that all these factors contribute, albeit differentially, to the variation in box-office performance (refer to Estimation section for detailed results on this). This descriptive analysis then motivates our model specification described in the subsequent section. The unit of analysis for the model is the consumer in a given local market area choosing from among a set of available movie-exhibitor combinations in that market and time period. The consumer can also choose the no-purchase option. Movie, exhibitor, market and temporal factors influence the consumer's discrete choice, which we characterize via a logit model. At the same time, we account for saturation effects in movie demand as well (Moul, 2005). Further, allowing for differences across consumers in their sensitivities to a variety of factors via a normal distribution yields the familiar random coefficients logit model that is then taken to the aggregate movie – time period – exhibitor – local market data. The section following the model description presents the empirical results. We then provide a section on model implications and conclude in a final section.

3. The Motion Picture Exhibitor Market

In this section we introduce the data used to estimate our proposed model (introduced in the next section) and provide an overview of the motion picture exhibition market. We hope that the stylized features presented in this section offer direction for future research in this area.

First, we describe the general characteristics of the motion picture industry obtained from other data sources and then we summarize the specific data that we use. Total revenue from the motion picture theatrical market in the United States was $8.95 billion in 2005. While movie demand in terms of number of tickets sold peaked in 2002 and has seen some decline since, box-office revenues peaked in 2004. As stated in the introduction, perhaps due to the lack of available data, there exists no research that has explored within the U.S. domestic market the geographic dimension and temporal aspects of motion picture demand. While understanding the role of geography is not new to marketing and dates back to studies as early as Huff (1963, 1964), recent studies like Bronnenberg et al. (2007) have fueled interest in documenting specific spatio-temporal aspects of consumer demand across different product categories.

The motion picture industry, however, is very different from consumer packaged goods analyzed by Bronnenberg et al. First, unlike most CPG products, movies are more akin to durable goods. Consumers who consume a specific movie are typically no longer in the market for the same good. Second, unlike simultaneous national-level roll-out of new brands within a retail account for CPG products (Bronnenberg and Mela 2004), exhibitor chains do not simultaneously roll out a new movie across all their theater outlets nationwide. In fact, there may exist differences in the motion picture distribution across theater chains (across exhibitor chains), within a theater chain (across geographic markets) and within a theater chain over time (temporal differences). Hence while there may be limited variation in the competitive set of brands in a CPG market within and/or across retailers and/or geographies, the shelf life of movie titles is small, and competitive sets could vary by chain, by market and over time. As stated in Ainslie et al. (2005), accounting for time-varying competitive sets is crucial to getting accurate forecasts of motion-picture demand.

We combine data from multiple data sources, both public and private, to generate a very unique and comprehensive theatrical movies database for the North American market (U.S. and Canada). The extant literature relies on national market-level weekly/monthly/annual title-specific box-office revenues[8]. We, on the other hand, observe exhibitor-level (theater) daily box-office revenues per movie title. Our data span 16 months beginning November 2003 until February 2005 and are expansive in terms of their coverage of exhibitors, exhibitor chains and movie titles for the time period. The data include: 4,273 exhibitor locations belonging to 332 exhibitor chains (includes independent theaters), and 836 movie titles spanning 209 A.C. Nielsen defined Designated Market Areas (DMAs). The sample consists of 12.08 million observations, where each observation is a movie-theater-day combination. Table 1 provides the cumulative gross distribution across top 20 titles. Notice that the top 20 titles alone account for 54.46 percent of total cumulative gross across all titles contained in our data. For each movie, we have characteristics like rating, genre, runtime, star power, movie critic ratings etc. that we collect. Ratings are classified as either NR (204 films), R (183), PG13 (116), PG (52), G (7) or NC17 (2). The top 10 genres in terms of number of movies released are drama (274 films), comedy (137), foreign (110), documentary (87), suspense (65), action (60), adventure (31), gay interest (31), romance (31) and horror (28). Sony, Warner Brothers and Buena Vista (Disney) were the top 3 distributors on both gross revenues and number of movies released. The largest exhibitor chain released 404 titles (due to confidentiality reasons we are unable to disclose chain identities), followed by others that released 377, 370, 327 movies, etc. Thus, we see that there is a fair bit of heterogeneity among movie titles on the attributes mentioned above.

[8] Davis (2005) is the notable exception.

We also collect information on the characteristics of the exhibitor. These include chain brand name, admission price[9], number of screens and geographic coordinates such as latitude and longitude. Table 2 describes the distribution of types of exhibitors in our data. Note that we a have good mix of uniplex, miniplex, multiplex and megaplex theaters. Uniplex are theaters with one screen. Miniplex are theaters with 2 to 7 screens, multiplex are theaters with 8 to 15 screens and theaters with more than 15 screens are deemed as megaplex theaters. Due to trends in the marketplace, there exist differences in supply of movies and screens across geographic markets and time. Our data also show considerable variation in cumulative gross, number of titles, number of screens and number of theaters across the top 20 geographic markets. In particular box office revenues from Los Angeles and New York exceed $600 million over the course of our data, with the next two largest markets being San Francisco and Chicago, with revenues between $250-300 million. All remaining markets had revenues less than $200 million. Together, the top 20 markets account for over 60% of all box-office revenues. In terms of number of theaters and screens, Los Angeles and New York once again lead the pack, with an average of 1,782 screens and 1,572 screens over the duration respectively (both from about an average of 200 theaters). By contrast, Chicago had an average of 900 screens and San Francisco about 674 screens. The variation in demand across markets can also result from demand-side differences (preference heterogeneity) and/or supply-side differences (heterogeneity in movie distribution) across markets. In order to accommodate observed heterogeneity in consumer response via demographics, we combine demographic data from the U.S. Census 2000 TIGER files. For each city-block market, we collect data on population, racial mix, income distribution, etc. The DMA-level descriptive statistics for our demographic variables are reported in Table 3. Thus, not only are box-office revenues concentrated around hit titles as previously stated (Table 1), but our data reveal that box-office revenues are also skewed across geographic markets. In our data, 17 percent of the total theatrical box-office revenues are generated by the top 20 titles across the top 20 markets alone. While our data contain information on locations in Canada as well, we limit our analysis to only U.S. locations. Notice from figure 1 that we have a very good distribution across markets. Figures 2 and 3 provide more detailed information for two select markets, i.e. Atlanta, GA, and Chicago, IL, respectively.[10] While previous research has shown that box-office revenues do vary by movie

[9] The exhibitor market practices uniform pricing across movies. However, it also practices price discrimination across showtimes (matinee vs. regular hours) or across consumer segments (student discounts, senior citizen discounts, regular price etc.). Since the revenues from non-regular adult price schedules are a very small fraction of the revenues from regular adult price, we only report the statistics for regular adult admission rates.

[10] In order to accommodate sequential rollout of a title across markets, we (a) introduce two indicator variables that denote opening day and opening weekend for a title within a focal market, (b) a variable that captures days since national release, and (c) days since release in local market.

characteristics, our data reveal that for any specific title, the box-office revenues it generates could also be spatially varying. Figure 4 reveals significant differences in box-office revenues across four movie titles across select DMAs. Similar patterns emerge for other titles. Such patterns suggest inclusion of market characteristics over and above movie characteristics in predicting box-office revenues. These spatially varying factors could include aforementioned variables such as a) time-invariant characteristics like demographics and b) time-varying local-market drivers like supply-side factors, spatially varying competitive sets, etc. Upon further investigation, our data reveal significant within-market variation. As is shown in Figure 5, title- specific box-office revenues vary by exhibitor chain within one select market (Atlanta, GA). Exclusive distributional rights in first-run showing may explain some of the cross-sectional difference within a market. In fact, for a given title and market, there exist differences in box-office revenues across exhibitor locations belonging to the same exhibitor chain. Figure 6 illustrates the cumulative box-office revenue differences for the movie *The Bourne Supremacy* in Atlanta, GA, across multiple theater locations of the same exhibitor chain for three chains. Since movies are novelty goods with short shelf lives, with the exception of a few titles, the box-office revenues for titles decay over time. Title-specific temporal decay in demand could vary by markets (due to the aforementioned factors). Figure 7 illustrates the spatio-temporal variation in daily box-office revenues for *The Bourne Supremacy* across five major markets.

Before we get to our structural model specification, we conduct some exploratory analysis to a variance decomposition of title-specific box office demand using some partial reduced-form equations. Doing so allows us to understand the marginal contribution of space, time and movie characteristics on title-specific demand. The results for the variance decomposition of movie demand are reported in Table 4. While previous research has looked at movie characteristics and temporal aspects of demand, our reduced-form results show that these factors only account for 40 percent [(10.47+15.5+8.4)/84] of the explained variance. Local-market factors that have so far been overlooked in the literature account for the majority of the explained variance (60 percent). Our reduced-form analysis merits further and more rigorous investigation of local market elements of movie demand.

To summarize, due the elements described earlier, it is crucial that managers take into account spatio-temporal aspects of the movie market along with the movie characteristics while forecasting title- specific demand. We attempt to do this via our model specification in the next section.

4. Model

In this section we discuss our model specification and lay out the assumptions made and their implications. The model proposed here relies on theater-level box-office sales across multiple movie titles shown across multiple exhibitors, observed over multiple time periods and across multiple geographic markets. As noted previously, our unit of analysis is an individual consumer (*i*) located in a given market (*g*), choosing among the various movie-exhibitor combinations (*je*) available to him/her on a given day (*t*), with the option of not watching any movie on that day. Based on this, we specify an aggregate logit model at the exhibitor-movie-day level by aggregating across heterogeneous consumers in that market. We rely on the estimation approach proposed in Berry et al. (1995) and Nevo (2000) that allows us to accommodate potential heterogeneity using our available aggregate-level data. At the same time, as in Ainslie at al, we allow for the competitive set to be specific to the geography and the time period.

Previous studies in marketing have used this approach to also accommodate correlation in price and structural error term, which proxies for any systematic omitted variables that affect both consumer demand and firm pricing decisions, but that are unobserved to the econometrician (Sudhir 2001, Dube' et al. 2005 etc.). In the movie industry, however, exhibitors engage in uniform pricing (Orbach and Einav, 2001) across movie titles. While there is price heterogeneity at the exhibitor-level, exhibitors do not change prices based on the composition of their daily/weekly movie assortment (Moul, 2005)[11]. Hence, unlike previously studied differentiated goods markets, in the movie industry price is less likely to be correlated with the structural error. At the same time, researchers have also found that an important driver of demand for a movie in a given time period is the time elapsed since the movie's launch (see also Elberse and Elaishberg 2004). If we included such a variable in our demand specification, we need to recognize that (unobserved) factors that affect demand at a location in a given time period could also influence how long, i.e., the number of time periods, that movie plays in that location. Hence how long a movie has been playing in a given market may be correlated with the error term in the demand function. It would be important to account for such correlation in the estimation of demand parameters.

Assume we observe G markets, where $g = 1,\ldots G$ and each market g is made up of M_g consumers. For each market, we observe daily box-office revenues for each movie title $j \in J_{egt}$ where J_{egt} is the time-varying set of movies running at exhibitor e in market g at time t. For each movie title, we observe characteristics like genre, star power, MPAA rating, critic ratings, etc. We denote this set of variables as

[11] Temporal price variation, while limited, is more likely reflective of changes in market structure, like exhibitor-level consolidations via mergers and or local market changes such as new entries, exits or changes in cost structure.

X_j. For each exhibitor, we observe characteristics like chain affiliation, admission prices, number of screens and geographic coordinates like latitude and longitude etc. We denote this set of variables as X_e. Consistent with previous research (e.g., Davis 2005), we define each designated market area (DMA) to be a market. In other words, we assume that consumers choose from movie-exhibitor combinations within the designated market area. The population of the DMA is then taken to be the potential market size. We carried out sensitivity analyses to alternative definitions of market area.

The utility of consumer *i* from consuming movie *j* at exhibitor *e* in market *g* at time *t*, U_{ijegt}, is a function of observed characteristics X_j, as well as movie- (*j*), exhibitor- (*e*) and time- (*t*) specific factors such as number of movies of the same genre as *j* running at time *t* at *e*, time since *j* was introduced at *e*. Together with the time-invariant factors (X_j), we denote all factors that are specific to a movie *j* by X_{jegt}. X_{jegt} also includes national advertising expenditures that vary by movie and time period, but do not vary by exhibitor or geographic market (X_{jt}); as well as local advertising expenditures that vary by geographic market, movie and time period (X_{jgt}). We define these variables more precisely later. U_{ijegt} can also be affected by theater-specific characteristics like number of new movies at *e*, chain affiliation, number of screens, etc. These are denoted by X_{egt} since they do not vary across consumers and movies. Again, some of these factors would be time-invariant exhibitor and geographic market factors. Let ξ_{jegt} denote the unobserved (to the researcher) characteristics like in-house promotion of the movie, number of screens in *e* running *j* at time *t*, etc.

More specifically,

$$U_{ijegt} = \theta_i X_{egt} + \beta_i X_{jegt} + \xi_{jegt} + \varepsilon_{ijegt} \qquad (1)$$

$X_{egt} = \{X_e, X_{eg}, X_t\}$
where
X_e: exhibitor chain affiliation, admission prices, number of screens, etc.
X_{eg}: distance from market centroid
X_{eg}: seasonality, day-of-week effect, etc.

$X_{jegt} = \{X_j, X_{jt}, X_{jgt}, X_{jegt}\}$
where
X_j: genre, star power, rating, etc.
X_{jt}: national advertising
X_{jgt}: local advertising
X_{jegt}: time since introduced at *e*, etc

where X_{jegt} is a *K* dimensional row vector and X_{egt} is an *L* dimensional row vector and ε_{ijegt} is a mean zero stochastic error term. Unlike X_{jegt} and X_{egt}, consistent with the previous literature, we assume that consumers respond homogeneously to ξ_{jegt} (Nevo 2001).

Next we discuss how we accommodate response heterogeneity. Heterogeneity may arise from observed consumer characteristics like income, age, race, etc. as well as from unobserved (to the econometrician) characteristics like size of household, category-specific budget constraint, availability of transportation to and from the movies, etc. If D_i denotes 'observed' characteristics of individual *i*, then

$$\begin{pmatrix}\beta_i \\ \theta_i\end{pmatrix} = \begin{pmatrix}\beta \\ \theta\end{pmatrix} + \Psi D_i + \Omega \upsilon_i \tag{2}$$

Where $\mathbf{\Psi}$ is a matrix of parameters of dimension (K+L)*d and D_i is of dimension d*1 and $\mathbf{\Omega}$ is a (K+L)*(K+L) dimensional matrix of parameters.

Therefore we can rewrite equation 1 as

$$\begin{aligned} U_{ijegt} &= \beta_i X_{jegt} + \theta_i X_{egt} + \xi_{jegt} + \varepsilon_{ijegt} \\ &= \left(X'_{jegt}\beta + X'_{egt}\theta + \xi_{jegt}\right) + \left[\left(X'_{jegt} + X'_{egt}\right)(\Psi D_i + \Omega \upsilon_i)\right] + \varepsilon_{ijegt} \\ &= \delta_{jegt} + \mu_{ijegt} + \varepsilon_{ijegt} \end{aligned} \tag{3}$$

where

$$\begin{aligned} &\delta_{jegt}(X'_{jegt}, X'_{egt}; \Theta_1) = \left(X'_{jegt}\beta + X'_{egt}\theta + \xi_{jegt}\right) \\ &\text{and} \\ &\mu_{ijegt}(X'_{jegt}, X'_{egt}, D, \upsilon; \Theta_2) = \left[\left(X'_{jegt} + X'_{egt}\right)(\Psi D_i + \Omega \upsilon_i)\right] \end{aligned} \tag{4}$$

The utility from the outside good, i.e. from not watching any movie that day, is given by

$$U_{iOgt} = \xi_{Ogt} + \mathbf{\Psi}_o D_i + \sigma_o \upsilon_{io} + \varepsilon_{iOgt} \tag{5}$$

Note, that $\xi_{Ogt}, \mathbf{\Psi}_o, \sigma_o$ cannot be separately identified. In order to normalize the utility from the outside good to be zero, we set $\xi_{Ogt} = \mathbf{\Psi}_o = \sigma_o = 0$.

The resulting title-exhibitor specific consumer choice probability is given by

$$P_{ijegt} = \frac{e^{\theta_i X_{egt} + \beta_i X_{jegt} + \xi_{jegt}}}{1 + \sum_{e=1}^{E_{gt}} \sum_{k=1}^{J_{et}} e^{\theta_i X_{egt} + \beta_i X_{kegt} + \xi_{kegt}}} = \frac{e^{(\theta X_{egt} + \beta X_{jegt} + \xi_{jegt}) + (\Delta\theta_i X_{egt} + \Delta\beta_i X_{jegt})}}{1 + \sum_{e=1}^{E_{gt}} \sum_{k=1}^{J_{et}} e^{\underbrace{(\theta X_{egt} + \beta X_{kegt} + \xi_{kegt})}_{\delta_{kegt}} + \underbrace{(\Delta\theta_i X_{egt} + \Delta\beta_i X_{kegt})}_{\Delta\mu_{ikegt}}}}$$

On any given day consumer *i* is assumed to consume only one unit of either one of the internal goods, i.e. one movie at any one exhibitor in a given market that day or the outside option. Assuming that ties occur with zero probability, the market share for movie *j* at exhibitor *e* in market *g* at time *t* is given by

$$s_{jegt}(X'_{jegt}, X'_{egt}, \delta_{jegt}; \Theta_2) = \int dP_{\varepsilon}(\varepsilon) dP_{\upsilon}(\upsilon) dP_{D}(D) \qquad (6)$$

Where $P_{\varepsilon}(\varepsilon)$ is the distribution of the random component of utility in equation (1); $P_{\upsilon}(\upsilon)$ denotes the distribution of the unobserved component of heterogeneity in equation (2); and $P_D(D)$ denotes the empirical distribution of demographics of the consumer population in that local market. Note that we need to integrate over the empirical distribution to account for observed heterogeneity since we do not observe data at the consumer level along with that consumer's demographics. Rather, we observe box-office performance in local markets for which we observe the distribution of demographics across residents. The title-exhibitor pair-level market shares are then computed from the daily box-office revenues at that location.

Implications of the Durable Nature of Movie Demand

As stated earlier, a unique feature of movie demand is that movies once consumed are unlikely to be considered in future consumption occasions. This feature of our market is unlike previous applications of the BLP framework to consumer packaged goods product markets where consumers may repeatedly consume the same good. Another issue as pointed out in Ainslie et al. (2005) is that the competitive set varies over time.

In our data (details provided in the next section), the daily consideration set for a representative consumer includes all movies running across multiple competing exhibitor locations within a certain market that have not been consumed till date. Since there are regional differences in movie distribution, consumers who have consumed the same movies till date but belong to different geographic markets may face different daily consideration sets. Hence our model complements the Ainslie et al. study in that we allow for the consideration set to vary spatially as well as temporally. These aforementioned unique features of the movie industry require us to take into account market-varying saturation effects for movie titles.

Moul (2005) provides a novel approach to accounting for saturation effects in demand. He proposes including $\ln(1-\lambda_{jgt})$ as a measure of title-specific saturation to δ_{jegt} where λ_{jgt} is the fraction of the total market that has consumed *j* in market *g* till date. Therefore:

$$\delta_{jegt}(X^{'}_{jegt}, X^{'}_{egt}; \Theta_1) = \left(X^{'}_{jegt}\beta + X^{'}_{egt}\theta + \xi_{jegt}\right) + \rho \ln(1-\lambda_{jgt}) \qquad (7)$$

This specification allows for consumer demand to reduce as more consumers in the same market consume the title, i.e. reducing residual demand for title over time. Holding everything constant, this demand specification allows for the highest purchase probability to occur earlier into the movie life-cycle than later. We direct readers to Moul (2005) for a detailed technical exposition.

Estimation

The estimation algorithm is described in the Appendix. Our estimation algorithm is akin to the one used in Nevo (2000) and Sudhir (2001) apart from the fact that, in our case, the choice sets vary over time by theater and by market. Recall from equation 1 that elements of X_{jegt} can potentially be correlated with ξ_{jegt} , hence we need to rely on instrumental variables to generate consistent estimates of our demand model parameters. Potentially correlated variables include admission prices (may be weakly correlated due to the practice of uniform pricing) and advertising spend (national and local). We therefore use admission prices in other markets of the same exhibitor chain, local advertising in other markets and lag national-level advertising as instruments in our empirical analysis. We also include exogenous variables including chain dummies and market dummies as potential instruments.

5. Variables

The variables included in our model as described above are $X_{jgt} = \{X_j, X_{jt}, X_{jg}, X_{jgt}\}$ and $X_{egt} = \{X_e, X_{eg}, X_t\}$. We discuss the specific variables constituting each of these sets below. Tables 5 through 7 describe and provide the variable listing and data source for the movie characteristics, exhibitor characteristics and market characteristics, respectively. Table 5 lists variables that differ by title. Some of these vary across titles (cross-sectional variation only, i.e. star power, genre, rating etc.), while some variables vary temporally within the same title (spatio-temporal variance, i.e. local and national advertising). Table 8 shows the descriptive statistics for our entire sample for the variables described in Tables 5 through Table 7. Note that there is sufficient variance in our data.

I. Title- specific variables (X_j)

a) Stars: Previous research (see Neelamegham and Chintagunta 1999, De Vany and Walls 1999, Ravid 1999) has pointed to the star power of a movie being an important characteristic driving the performance of a movie. Accordingly, we use a measure of a title's star power as a factor influencing the movie's box-office performance. The specific measure we use is the number of members of the cast and crew that are featured as part of the top 100 entertainers by the publication *Hollywood Reporter*. This definition is used by movie studios and distributors and was given to us by our data provider.

b) Critic evaluation: As with some of our other measures used here, empirical research has found mixed results for the impact of the evaluation of a movie by film critics on box office performance of the title (see Eliashberg and Shugan 1997, Jedidi et al. 1998, Ravid 1999, Zufryden 2000). Nevertheless, it continues to be an important characteristic used by researchers when looking at a title's market performance. Here, we use a movie's Meta Score from *Metacritic.com* (http://www.metacritic.com/about/scoring.shtml). The score represents a weighted average of critic scores from about 30 top publications and critics, with higher scores reflecting higher ratings. The scores range from 0-100.

c) Runtime (in minutes): Ainslie, Dreze and Zufryden (2005) include the running reel time of a movie to distinguish between blockbusters (that typically have longer run times) and more arty films that tend to have shorter run times. Consistent with their observation, in our data, too, we find significant variation in cumulative box-office gross by run time. Figure 8 graphically illustrates the variation in box-office gross by runtime and frequency of number of titles by run time. Hence, we treat this variable (a title-specific characteristic) as a potential influencer of movie performance, and include it in our analysis.

d) Genre: In line with previous research (see Elberse and Eliashberg 2005, De Vany and Walls 1999, Ravid 1999), we include the title's genre as one of the movie's characteristics. We have 11 levels of this variable – comedy, drama, action, romantic comedy, suspense, horror, fantasy, animation, science fiction, adventure and others (base). The descriptive statistics on this variable have been summarized in Table 9.

e) Rating: While some researchers have included the MPAA rating of a movie as a title's characteristic (De Vany and Walls 2002), others such as Ainslie et al. use the number of movies with the same MPAA rating that were launched at the same time as the movie in consideration as a predictor of relative movie performance (see also Ravid and Basuroy 1999). We include 6 levels of this variable – NR, G, PG, PG13, R and NC17 (base), and summarize the descriptives in Table 10.

f) Distributor: As in previous studies (e.g., Elberse and Eliashberg 2003), we include distributor dummies for Sony-Columbia, Buena Vista, Warner Bros., 20th Century Fox, Universal, Paramount, Dreamworks SKG, New Line, Miramax, MGM, and others (base). This variable is included to capture factors specific to the organization distributing the film. The descriptive statistics on this variable have been summarized in Tables 11a and 11b.

II. *Titl -and time- specific variables (X_{jt})*

a) National advertising expenditures: The importance of advertising has been underscored in previous studies such as Lehmann and Weinberg 2000, Moul 2001, Elberse and Anand 2007. Our raw advertising data are at the level of title-month-advertising medium. First, since some media are national (network TV, national magazines and newspapers, Internet, etc.), whereas others are local (spot TV, local magazines and newspapers), we aggregated the data into title-month national and local advertising. Next, we appropriated the monthly spends on the movie to daily spends by using the decay rate from the monthly spending pattern and applying it to daily spends within the month. We then used these daily spends (in logarithmic form after adding 1) as drivers of box-office performance. Since distributors spend on movie advertising prior to the theatrical release of the movie, we use the total expenditures prior to a movie's release as drivers of opening-weekend box-office performance. We used the same procedure for national and local advertising. We checked for the sensitivity of our results to alternative appropriation schemes, as well as to defining the advertising variables as flows or stocks. While these different operationalizations yielded somewhat different point estimates, the nature of our results, especially for the other parameters included in the model, was unaffected. Hence, we report the results from the simple operationalization here. Descriptive statistics for the advertising data are in Table 8.

b) Time since national release. There have been several reasons given for including this variable in aggregate movie demand models. In particular, this variable could represent the level of interest/wearout in the movie, aggregate word-of-mouth effects or even saturation effects at the national level. Previous researchers (e.g., Elberse and Eliashberg, 2003) have found this variable to play a role in generating aggregate movie forecasts when movies are sequentially released across markets.

III. ***Title- and market- specific variables (X_{jg})***

a) Opening-day dummy: We include this dummy variable to capture any demand beyond what we might expect from the various movie characteristics, seasonality and day-of-week (as most movies are released on Fridays) effects. Typically, pent-up demand for a movie based on the advertising levels prior to release might result in more traffic for the movie on the opening day in a given market. We include this variable to capture that effect.

b) Opening-weekend dummy: Similar to the opening-day effect above, this variable accounts for demand patterns specific to the first weekend of the movie in that market for the reasons already noted.

IV. ***Title-, market- and time- specific variables (X_{jgt})***

a) Local advertising expenditures: This is defined above in the section on national advertising expenditures. We note that while previous researchers have pointed out the importance of advertising (Zufryden, 1996; Elberse and Anand, 2005) and others have used measures of advertising in their analysis of box-office performance (e.g., Ainslie et al. 2005), our data are perhaps the most comprehensive since they distinguish between advertising in national versus local media. Obviously, the latter spending varies by geography, and could be a determinant of the geographic variation in a movie's box-office performance. We graphically illustrate the within-title-across-market AND across-title-across-market distribution in local advertising expenditures in Figures 9 through 11.

b) Saturation effects: Moul (2003) points out the importance of accounting for the "durable good nature" of the movie market. In other words, once a consumer has watched a particular movie, it reduces the probability of that consumer viewing the movie again. He suggests using the operationalization "*ln*(1 – proportion in the local market that has already seen the movie)" to capture the saturation effect at each time period for each title. Accordingly, we use this operationalization to account for this title-, market- and time-specific variable.

c) Days since the title (*j*) was launched in that market (*g*). The longer a movie runs in a particular market, the lower is likely to be its attractiveness to the target market (see also Neelamegham and Chintagunta 1997). The inclusion of this variable captures the possible "drop off" of a movie's box office beyond the initial release days for movies released under a wide release strategy where a large number of screens are used at the time of initial release – a factor that studios closely monitor (see Elberse and Eliashberg 2003).

V. *Title-, exhibitor-, market- and time- specific variables* (X_{jegt})

a) Days since the title (*j*) began screening at exhibitor (*e*) in that market (*g*). Similar to the above variable, the longer a movie runs at a particular exhibitor, the lower is likely to be its attractiveness to local market of that exhibitor. Thus the inclusion of this variable captures the possible "drop off" of a movie's box office beyond the initial release days for that exhibitor over and above the effect at the entire market level.

b) Cumulative box-office for movie (*j*) at that exhibitor (*e*). As in Neelamegham and Chintagunta (1999), this variable is included to capture word-of-mouth effects. This specification appeared to do a better job than including just the corresponding market level variable instead.

VI. *Exhibitor- specific variables* (X_e , X_{eg})

a) Chain (exhibitor) fixed effects. To capture differences in theater chains that could enhance or lower their attractiveness to consumers, we include chain fixed effects. These variables capture unobserved chain-specific characteristics such as stadium seating, loyalty programs, etc. – factors that do not vary over time or across movie titles.

b) Admission price. Different exhibitors charge different prices, with these differences particularly marked between first-run and second-run theaters. We use the admission price at an exhibitor that corresponds to the adult regular ticket price to capture such variations across exhibitors. We are able to identify this effect beyond the chain fixed effects since admission price also varies across geographic markets for the same chain. See also Davis (2005), who has used admission price as a variable.

c) Number of screens at that location. This is another factor that can make a particular exhibitor more attractive in the minds of consumers. The larger the number of screens available at a particular exhibitor location, the greater is the variety of films available to the consumer to watch. This in turn could make that location more attractive to the consumer.

d) Distance of exhibitor from the market centroid. For an individual consumer, a critical driver of retail location choice is the distance of the consumer from the retailer's location (see, for example, Bell, Ho and Tang 1998). The movie exhibitor market is similar in this regard. Consequently, researchers (see Davis 2005) have attempted to capture the distance between consumers and the theater location in their demand models. However, the data available to us are aggregate in nature, so individual consumer locations are not available. One approach to addressing this issue is to simulate from the joint density of consumers in a given market area to come up with a distribution of distances over which individual choices can be integrated to obtain market demand (see Davis 2005; Houde 2006; for a similar strategy). However, carrying out this exercise for all the movie theaters in the United States is an extremely onerous task. As a simplification, we use the distance of a movie theater from the market centroid to capture how far that exhibitor is located from the "average" location at that market. Of course, it is possible that the centroid of the market has in some cases many consumers, whereas in other cases it might have very few consumers. To capture such variation, the effect of the distance from the centroid on the attractiveness of a title at a particular exhibitor is allowed to be heterogeneous across markets[12].

VII. *Time- specific effects* (X_t)

a) Seasonal effects. Other researchers (notably Einav 2003a and 2003b) have shown that there are seasonal effects to the ticket sales of movies. Specifically, summer months that also coincide with the release of blockbusters show an increase in sales over other months of the year. Further, months that include major holidays (e.g., Memorial Day) are also likely to see increased sales levels. As discussed above, our model already controls for movie characteristics. In addition, we include a dummy variable for each week in the year in our data (week 1 to week 52) to reflect variation in sales over time (the weekly dummies are identified since we have daily data and thus 7 observations for a given week with a year's worth of data). Further, as our data span two years, we have a year dummy (for 2004 with year 2003 = 0).

b) Day-of-week effect. Similar to the seasonal effect discussed above, there are strong day-of-week effects. Consumers have greater leisure time over the weekend that draws them more to movie theaters. To capture such day-of-week effects, we include a day-of-week dummy in the model. See also Davis (2005). Further, we include a dummy variable for the major holidays such as Martin Luther King Day, Presidents Day, Memorial Day, Christmas, Independence Day, Election Day, Thanksgiving and Columbus Day.

[12] An alternative approach would be to draw a representative sample of households and for each household compute the distances to each theater in the chosen market. This approach is slightly more cumbersome than our current approach. Like the centroid-based approach we take, the individual-distances-based approach would also require us to make the assumption that all consumers consider all locations. For a random set of 10 markets where we were able to accurately extract the tract-level information, we conducted the analysis using the individual-level distance measures. While our estimates changed slightly, the substantive implications did not change very much. Furthermore, this approach took much longer to converge and resulted in less accurate in-sample and out-of-sample predictions. Taking these into consideration, we reverted to the centroid-based approach and report our results accordingly.

In addition to the above variables, we include several demographic variables, D_i to account for the impact of observable heterogeneity on demand [see equation (2)]. Individual-level demographic variables are obtained from the U.S. Census-based TIGER files. For each market, we draw 1,000 individuals from the empirical distribution of demographics in each geographic market. The demographic variables we include are: income, whether household is African-American, whether household is Hispanic. While the data are extracted at the census tract-level, we report the market-level descriptive statistics in Table 3.

VIII. ***Market- specific effects*** **(X_g)**

a) Market-specific effects. There may exist systematic differences across geographic markets that are not accounted for by our demographic variables alone. Hence we include DMA fixed effects in our model. This enters only in the calculation of the mean utility, i.e. δ_{jegt} and not μ_{ijegt}.

6. Empirical results

We begin by discussing the parameter estimates corresponding to the various variables above. We note that in the empirical analysis, we use the first 14 months as the estimation period and last two months as the hold-out period. After presenting the parameter estimates, we discuss the implications of these results for distributors and exhibitors. The parameter estimates (and their t-statistics) are in Tables 12 through 13. The table provides the estimates from the proposed heterogeneous (mixed) logit model. We provide both the mean parameter estimates ($\boldsymbol{\delta}_{\mathbf{jegt}}$) and the interaction effects with the demographic variables ($\mathbf{D}_{ig}$). Recall that the demographic variables are mean-centered, and that the reported demographic effects represent deviation from the mean effect.[13]

I. ***Title- specific variables (X_j)***

a) Stars: As expected, the demand for a movie is enhanced by the presence of star power. This is consistent with previous studies that have looked at the impact of movie "attributes" on demand (Levin and Levin 1997; Albert 1998; De Vany and Walls 1999). We also find that the effect of the number of stars is enhanced for high-income, but is diminished for African-American and Hispanic households relative to Caucasian households.

[13] Given the large numbers of indicator variables included in the analysis, especially for seasonal effects (weekly dummies) and day of week effects, we do not report those estimates here. Further, for variables such as genre, distributor, chain etc., we only report the estimates for those in each category that are most frequent in our data.

b) Critic evaluation: As with studies such as Eliashberg and Shugan (1997), we find that the better the critics' reviews (specifically pre-release critic reviews), the higher the demand for a movie. At the same time, this does not address the criticism raised by these researchers that critics' reviews tend to be better for better movies, so some caution needs to be exercised while interpreting these results. Critic reviews have more of an effect for higher income households, but the effect is lower for African-American and Hispanic households relative to their Caucasian peers.

c) Run time (in minutes): Consistent with the notion that blockbusters tend to have longer run times than art-house movies, we find that the mean effect of run time on demand is positive. At the same time, higher income households have a lower preference for longer run time movies, possibly due to higher opportunity costs of time (Ainslie et al. 2005). Controlling for income levels, it appears that African-American households have a higher preference for longer movies than Caucasian households who have a higher preference than Hispanic households.

d) Genre: We only present the results for the top 10 genres in the Table. For those, we find that the genres of documentary and gay interest seem to have the highest demand after controlling for all other factors. While it is hard to interpret the results of a specific genre, there is certainly evidence for considerable heterogeneity in the preferences for the genres as well. Again, this finding is very much in line with previous studies on the movies market. In terms of the demographic interactions, we find some interesting patterns as well. For example, higher-income households have a higher preference than average for dramas, foreign, romance, comedy and action films. African-American households have higher preferences than average for adventure and horror movies, whereas Hispanic households have higher a preference for the drama, action, romance and foreign genres.

e) Rating: After controlling for all other factors in the analysis, we find that G-rated movies have the highest preference, followed by NC 17-, PG13-, NR- and R-rated movies. With the possible exception of the "NC17" rating for which there were very few films released, and to some extent the G rating, this seems to be consistent with the notion that demand is higher for movies with ratings that allow a larger audience to watch the movie. High income households appear to have the highest preference for NC17 titles, followed by R- and NR-rated titles and the lowest preference for G-rated titles.

f) Distributor: Our results indicate that consumers have a higher intrinsic preference for movies released by Sony, Warner, Universal and Paramount among the larger studios relative to the "others" category. Higher income households appear to prefer Buena Vista (Disney) movies, consistent with their higher preferences for G-rated movies, as well as Universal and Sony Pictures Classics movies. Hispanic households appear to prefer movies from Sony, 20th Century Fox and Universal, whereas African-American households have a higher preference than average for movies released by most studios.

II. *Title- and time- specific variables (X_{jt})*

a) National advertising expenditures: We find statistically significant mean effects of national advertising on exhibitor-level demand for a movie. Further, we find that higher-income neighborhoods are more sensitive to such advertising. In addition, these effects are attenuated in African-American neighborhoods and in Hispanic neighborhoods. In terms of the marginal effects of such advertising, we computed a measure of advertising elasticity for each observation in our data and then averaged across observations. The computed short-term advertising elasticity was .063 for national-level advertising spends which is much smaller than the elasticity reported in Luan and Sudhir (2007) and more in line with the elasticity reported in Sethuraman and Tellis (1991).

b) Time since national release: Consistent with previous literature, we find that the longer the time since national release, the lower is the demand for the movie in a market. This variable probably reflects the overall "newness" of the movie and as that declines with time, it correspondingly lowers the interest in, and hence demand for, the movie. Furthermore, this decline in interest is highest amongst African-Americans followed by Hispanic households relative to Causasian households.

III *Title- and market-specific variables (X_{jg})*

a) and b) Opening-day and opening-weekend dummy variables: We find that for a given market the opening-weekend indicator has a strong positive impact on box-office performance. However, we find that the opening-day dummy variable has a negative impact on box office after controlling for all other factors in the model. The negative effect could in part be because many of the titles are released on Thursday night, while Friday and Saturday are peak demand days.

IV. *Title-, market- and time-specific variables (X_{jgt})*

a) Local advertising expenditures: As with national advertising, we find that local advertising also has a positive and statistically significant effect on exhibitor demand. Unlike the effects of national advertising, we find that local advertising is less effective in higher-income neighborhoods. At the same time, neighborhoods with a higher presence of African-American families show a larger effect of local advertising, and the effects of such advertising are even larger in neighborhoods with a higher proportion of Hispanic households. The computed short-term local advertising elasticity is .023, which is a third of the average national-level elasticity.

b) Saturation effects: From Table 13, we see that the coefficient of the saturation variable is positive and statistically significant at the 5 percent level of significance. This indicates that the box-office ticket sales on any given day are proportional to the remaining potential market for that movie. Thus, as more and more viewers in a market see a movie, the smaller is the effect of this variable on box-office sales of the movie. One possible countervailing effect that can also be reflected in this variable is that of word-of-mouth. Note that word-of-mouth effects should get larger as more consumers in a market view a film. However, our estimated effect is the opposite. This indicates that, for these data, the effects of saturation may be larger than the effects of word-of-mouth. We note that previous research (e.g., Neelamegham and Chintagunta 1999) has found a similar effect as well. At the same time, we also allow for a variable that could reflect word-of-mouth effects at the exhibitor level, the results for which are discussed later.

c) Days since the title (*j*) was launched in that market (*g*). Consistent with prior expectations, we find that as more days elapse from the movie's introduction in a particular market, the lower will be the demand for that movie. This is consistent with the life cycle often attributed to movies (see for example Elberse and Eliashberg 2003). It is important to note that the phenomenon also occurs at the level of the local market, beyond being a national-level phenomenon. Further, we find that the effect is accentuated for high-income neighborhoods.

V. *Title-, market-, exhibitor- and time-specific variables (X_{jegt})*

a) Time since release of title (*j*) playing at that exhibitor (*e*) at that time period (*t*). As with the national and local market time-since-release variables, we once again find a negative effect at the exhibitor level of the duration that the movie has been playing at that market and at that exhibitor. The demographic interactions, however, are more similar to the local market time effects. Thus there is a drop-off in a movie's demand over time even at the theater level.

b) Cumulative box-office for movie (*j*) at that exhibitor (*e*). We find a strong positive effect of this lagged variable on current period box-office performance of a movie. After controlling for all other effects described above, this variable appears to account for local word-of-mouth effects in the market beyond the effects reflected in the saturation variable. We also find that the effect is enhanced for higher income and for African-American neighborhoods.

VI. ***Exhibitor specific variables*** (X_e , X_{eg})

a) Chain fixed effects. Like their preference for distributors, consumers are also heterogeneous in their preference for exhibitor chains. Mean-differenced baseline preferences for exhibitor chains also differs significantly relative to the "others" option.

b) Admission price. Consistent with the finding in Davis (2005), Table 13 indicates that price has a negative and statistically significant effect on box-office receipts. Subsequently, we will compute the corresponding price elasticity. The mean price elasticity is 0.15. A point to note here is that both high-income and minority households are more price-sensitive than their counterparts.

c) Number of screens at that location. Our results for this variable indicate that an exhibitor can draw a larger number of viewers to its location when there are a large number of screens at that location. Two effects are possible: first, the overall number of seats at a location can be higher the larger the number of screens; second, more screens allows the exhibitor to display a wider variety of movies at that location. The number of screens seems to matter less at higher income-levels (maybe because more screen results in more crowding and less privacy). The same effect holds for minority neighborhoods. If the number of screens proxies for the variety of the exhibitor's assortment, then our empirical results suggests that variety matters more to Caucasians than minorities.

d) Distance of exhibitor from the market centroid. As expected, we find that the greater the distance an exhibitor is from the centroid of the market, the lower will be the box-office revenues for the movies playing at that exhibitor's location. Our interpretation of this finding is that it is the net outcome of two potentially opposing forces. On average, locating at the centroid gives the exhibitor access to a larger group of potential customers. Thus, one would expect that a move away from the centroid would lower demand. On the other hand, it is also likely that there are more exhibitors located at the market centroid, thereby raising the level of competitive intensity across exhibitors. The net effect, according to our parameter estimates, is that the competitive or business-stealing effect is smaller than the larger potential market effect closer to the market's centroid. Consequently, locating farther away from the centroid lowers box-office performance.

VII. ***Time-specific effects*** (X_t)

a) Seasonal effects and b) Day-of-week effect. As noted previously, we do not report the individual estimates here. Suffice it to note here that our results indicate that the three days of the week with the highest demand are Saturday, Friday and Sunday, in that order. The annual dummy indicates that the demand in 2004 was lower than the demand in 2003. This finding is consistent with industry reports that suggest that people are foregoing the cinemas for other alternatives such as video rentals, pay-per-view, video games, etc. The weekly dummy variables, while exhibiting variation in demand across weeks, do not reveal any specific patterns to the demand.

VIII. *Market-specific effects* (X_g)

a) DMA Fixed Effects: As noted previously, we do not report the individual estimates here. Suffice it to note here that our results indicate significant variation across DMAs. However, the results do not reveal any specific patterns to the demand.

To summarize the estimates of our demand model, we find that national-level factors (such as advertising) and factors specific to the local market as well as to the theater (i.e., chain / exhibitor) play an important role in determining daily demand for movies. Obviously, these latter factors are masked when one looks only at national aggregated data. Next, we provide a comparison of our results to those obtained from an alternative specification of demand at the national-market level.

Model Comparison with an Aggregate Demand Specification

As stated in the previous section, our rich database allows us to analyze movie demand at a very disaggregate level – i.e. at the individual-exhibitor level. However, the extant literature in marketing has estimated movie demand models (either title-specific demand or title-specific market share model) using national-level aggregate data.

If researchers and/or managers had access to only national-level data, while in reality consumer choice and hence competitive interactions are regional (as assumed in the model we propose), it would be valuable to assess the differences in results across aggregate-level and disaggregate-level demand models. Since the parameter estimates might themselves not be directly comparable, we rely instead on overall in-sample and out-of-sample model fit across the two specifications as the bases for comparison.

To carry out the comparison, we first aggregate exhibitor-level daily title sales up to the national level. The size of the potential market is taken to be the sum of the populations of the DMAs included in our disaggregate model. We use national-level counterparts of the explanatory variables used in our previously described model to predict daily title-level market shares. Note that national-level aggregation limits the set of predictor variables to: a) title-specific time-invariant characteristics (movie attributes), b) title-specific time-varying characteristics, and c) seasonality-control variables. Market specific variables cannot be included in the analysis. Table 14 lists the variables (the national-level counterparts) included in both the national-level and exhibitor-level demand models and those that are excluded from the national-level demand model.

Since our national-level model is a market-share model, it is closest in spirit to Ainslie et al. (2005) in that both models account for substitution across titles while taking into account the time-varying nature of choice sets. Notable areas of departure from Ainslie et al. are due to our inclusion of the following variables in the analysis: a) title-specific saturation b) advertising spends (local and national), and c) unobserved consumer heterogeneity in the analysis. Note, however, that while our disaggregate model accounted for observable heterogeneity (via demographics) as well as for unobserved heterogeneity via υ in equation 2, the aggregate analysis only accounts for the unobserved heterogeneity component. Importantly, while those authors use a Bayesian estimation approach, we retain comparability with our proposed model using a classical approach to parameter estimation. We provide the mean estimates of our national-level aggregate demand model (henceforth called Ainslie et al. model) in Table 15.

The parameter estimates across the two model specifications are not directly comparable. Thus, we focus instead on the qualitative nature of the results obtained. First, of the movie time invariant characteristics, we note that the signs of the effects of run-time, critic valuations, genre and rating are the same across the two models. The one exception appears to be the variable "starpower," which has a positive effect in the disaggregate model but a negative effect in the aggregate model. Other than that, the qualitative nature of the results are very similar across the two model specifications. Further, variables specific to the aggregate model (e.g., number of locations at which the movie is playing, an important predictor in previous analyses of box-office revenues) appear to have qualitatively reasonable estimates as well.

Table 15 indicates that the fit of the aggregate model is quite comparable to the fit of such models published in the previous literature (see for example, Neelamegham and Chintagunta, 1999). More importantly, it appears that the proposed disaggregate model provides a better prediction of the aggregate shares both within sample as well as in a holdout sample period. What might be some reasons for this difference?

As stated in previous sections, there are significant differences in movie distribution across markets and over time. Aggregating the time series to the national-level forces the researcher to make the erroneous assumption that all titles are available to all consumers across all markets as soon as the movie is released. Note that if movies are rolled out sequentially across markets, in the aggregate we will observe continued sales growth/maintenance arising from demand generated in new markets that the movie is being rolled-out into sequentially in the disaggregate data. Figure 12 shows the heterogeneity that exists in roll-out strategies across select titles in our data. Aggregating to the national-level time series can introduce undesired aggregation bias.

Note that the mean effects of several of the movie time-invariant and time-varying characteristics are different in the two model specifications. These differences have a significant impact on practice since firms often make decisions like green-lighting projects (Eliashberg et al. 2007), signing up stars as well their pre-release and post-release advertising levels. For example, elasticity estimates for national and local advertising using the aggregate model are .88 and .94, respectively. As reported previously, the corresponding elasticities from our proposed model are .06 and .023, respectively. Our results suggests that failure to account for local market factors can result in over-stated advertising effects. Furthermore, the relative magnitude of the effects are opposite across the aggregate and disaggregate models.

In the disaggregate model, across-market differences in the effectiveness of marketing instruments, movie and movie-market characteristics are modeled via interacted market-level demographics. However, in the national-level model, these effects are captured only via unobserved heterogeneity in demand-side parameters via υ in equation 2. In the absence of these demographic covariates, our national-level model could generate biased mean-parameter estimates.

While the model fit and predictive ability in Table 15 were assessed across all movies in the estimation and holdout sample, we also computed these metrics at the individual-movie-title level. We find that for *94 percent* of the titles in the estimation sample and *91 percent* of the titles in the hold-out sample, our exhibitor-level model-based predictions outperform the aggregate-model counterparts. This further reinforces our findings in favor of the proposed model.

7. Counterfactuals – Assessing the impact of exhibitor-level price competition and gains from advertising

Exhibitor chains make several decisions that impact their revenues. Principally, among these decisions, they set the ticket prices for the movies playing in their theaters, decide on the levels of local advertising support, and determine the duration of a movie’s run (subject to the contractual obligations imposed by the distributor). Accordingly, in this section, we conduct three counterfactual experiments corresponding to these three decisions. In particular, we try to quantify the effect of: a) an exhibitor chain’s price hike in a given geographic market, b) reallocating current advertising levels between national and local advertising in conjunction with the distributors, and c) running a given movie title for an additional day in lieu of running the lowest-revenue-generating movie at that location for that day. All three experiments are carried out for three specific geographic markets – Atlanta, GA; Dallas, TX; and Seattle, WA.

I. Counterfactuals 1a and 1b - Exhibitor's Price Change:

Our model formulation also enables us to compute metrics such as price elasticities and also carry out experiments in which the admission prices are varied either at the individual-theater level, account level, market-level or nationwide. While we focus only on a couple of experiments here, others are also straightforward to carry out.

Our objective here is to simulate the change in market shares under two scenarios namely

a) a theater within a geographic market were to increase its admission ticket price by one dollar,

or

b) an exhibitor chain were to increase its admission ticket price across all its locations nationwide by one dollar

In order to do this, we chose the top 5 exhibitor chains in three select markets (the same 5 chains were the market leaders across all three markets) and increased admissions price by $1 either at one theater or at all theater locations of a focal exhibitor chain. In other words, we increased the price at one exhibitor by one dollar and computed the percentage change in share for each of the 5 exhibitors across all their theater locations in that market. We then repeated this process for each of the 5 chains in that market. This procedure was repeated for all three geographic markets.

Table 17 provides the appropriate measures when prices are changed at the level of an individual theater, i.e. a. The results in the table show that the markets are quite different in terms of the percentage change in shares for a dollar change in price. In the Atlanta market, the own-effects of price range from -3.89 to -0.15; in the Dallas market they range from -3.75 to -0.28; in the Seattle market they range from –2.76 to -0.37. Thus it appears that exhibitors in the Dallas market are the most sensitive to an increase in the admission price by a dollar. Clearly, these differences reflect not only differences in average price levels across markets but also on other factors such as the set of exhibitors competing in each market, the set of movies playing in these markets, etc. The second feature to note from the table is that there is considerable variation in price sensitivity across chains within a market. A third feature of the results in the table is that the nature of rivalry across chains is asymmetric and also varies across markets. Similar conclusions can be drawn regarding the nature of inter-chain competition in other markets as well.

Table 18 provides the appropriate measures when prices are changed across all locations belonging to the same exhibitor chain, i.e. b. The above analysis was carried out at the level of the geographic market wherein each exhibitor chain changed its prices. Our data also enable us to compute the elasticities across specific theater locations when the chain changes its price for the entire market. This will tell us, at a very micro level, the impact of a price change on a location. In table 18 we present these location-level elasticities for the top 5 theaters in each market. Note that these locations need not be geographically proximal to one another; they have been chosen purely based on their revenues. The table shows that the nature of competition across chains varies across markets and, much like a. is also asymmetric.

II. Counterfactuals 2a and 2b - Advertising Policy Change

The previous counterfactual dealt with a change in price. Next we turn to another variable in the control of distributors and exhibitors – advertising. Typically, distributors determine national-advertising levels and provide cooperative advertising support for local-advertising. Further, exhibitors in specific geographic markets can also invest in local advertising efforts. In carrying out the advertising experiments vis-à-vis the three markets of interest, we will assume that distributors and exhibitors can come together and reallocate the advertising dollars as we describe below. The two scenarios we examine are:

a. directing the current national-advertising spend to the local level by proportionally allocating based on the current local-advertising spend

or

b. directing all of the current local-advertising spend to the current national advertising

In a. above, we take the current national advertising spend for each movie and proportionally reallocate it (using current local-level advertising spend for that movie) to the current local-advertising spend in these three markets. We do this for all titles belonging to a focal distributor. We then "zeroed out" the national-advertising level. The resulting market share for the distributor's movies in that market are then used to compute the mean percentage change in market shares for the distributor in that market. These changes, computed for each of the top 5 distributors in each market, are provided in Table 19.

The results in Table 19 show that the own effects of the reallocation are such that distributors are uniformly worse off with the proposed reallocation. Recall that the coefficient and the elasticity of local advertising is lower than that for national advertising and note that only a proportion of national advertising is being allocated to the local level in each of the three markets. This proportion is small relative to the overall national spend, and the lower local advertising coefficient cannot compensate for the difference. Second, we note that there is considerable heterogeneity in effects both across distributors and across markets. In looking at the table, we find that Atlanta appears to be both quite price- and advertising-sensitive. Third, competing distributors gain differentially in the three markets when a focal distributor re-allocates its advertising expenditures. This implies that the nature of advertising competition across distributors is market-specific.

Next, we looked at the situation in which all the local advertising dollars are re-allocated to national advertising. In b. above, we took all the money that a distributor spends on local advertising for all its movies across the three chosen markets and added this amount to the observed national advertising spend during the same period. We then treat this as the “new” national-level advertising amount, and “zeroed out” the local advertising spend in each market. The resulting market share for the distributor’s movies in that market were then used to compute the mean percentage change in market share for the distributor in that market. These changes, computed for each of the top 5 distributors in each market, are provided in Table 20.

The results in Table 20 show the own and cross effects of such a reallocation of advertising spends. Here, too, distributors are uniformly worse off with an all-national advertising strategy. Here, too, the competitive effects of the reallocation are quite heterogeneous across the 5 distributors.

To summarize, our results indicate that either an “*All National*” strategy or an “*All Local*” advertising strategy do not afford additional market share for distributors. One potential reason for this effect are the rollout strategies employed by distributors in the motion-picture industry. Another potential reason can be synergies between the two advertising investments. Given the descriptive focus of this study, we have not accounted for such synergies. However, any future research that focuses on optimizing advertising spend across local and national advertising for the motion-picture industry needs to account for such synergies.

III. Counterfactual 3 - Changing the duration of a movie’s run at a theater location

In this experiment, we focus on a specific theater location. We then ask the question: What would be the implications for a theater’s revenues if instead of replacing a movie that was actually replaced (in the data) when a new film is released, to managers replaced the movie with the lowest revenues? For this, we looked at the movies’ revenues on the day before the new movie was released. Worst-performing title/s may not necessarily be replaced for several reasons. These could include (but are not limited to) contractual obligations with distributors on screening spells or more attractive vertical contracting arrangements.

Here, for a specific theater, we indentify the worst-performing title/s (on the day prior to the release of a new movie) and all non-worst-performing titles that the exhibitor stopped screening in the data post release of a new movie/s. For each combination of a *worst-performing title*non-worst-performing title,* i.e. dropping the worst-performing title and keeping the non-worst-performing title, we simulate the daily market shares per title, and aggregate these to generate theater-level market shares and daily theater-level revenues. We compare the simulated daily metrics against the observed daily metrics. We generate total change (over the entire spell), and then average these across all titles per theater location. We repeat this procedure across all locations with a market and across the three geographic markets. These changes, computed for each of the top 5 exhibitors in each market, are provided in Table 21.

The results in Table 21 show the own and cross effects of such product-line replacements. Notice that it does not always help a theater to replace the worst-performing title, notwithstanding any contractual obligations. This is because our replacement heuristic is myopic in that it could lead to the replacement of sleeper hits and the retention of titles that do not perform as well in the long-run. Here, too, the effects vary by theater and by market.

Our results provide some valuable insights to theater managers when it comes to managing their product lines. Our results suggest that any future research that focuses on optimizing product lines at the exhibitor level needs to account for long-run objectives.

8. **Conclusion**

In this paper, we have proposed an exhibitor-level demand model as an alternative to the national-level demand model to forecast daily demand of competing films in an oligopolistic U.S. motion-picture exhibitor market. While previous national-level models have accounted for the strength of distribution of a title (i.e. the number of screens where the title in being screened), they fail to account for the composition of the exhibitors screening the title. In the motion-picture business, consumer demand is influenced by the choice of titles available to the consumer at the exhibitors in his/her market. Since not all movies are available in all geographic markets at the same time, failure to account for this can result in aggregation-bias. The proposed model addresses this gap in the literature.

The primary benefit that accrues from using our proposed model is its ability to account for competition amongst movie titles being screened in a market, by separately accounting for competition between titles screened at the same exhibitor and across exhibitors in the same market. We also parse out the effects of national-level and local-level advertising spends on movie demand. Our demand specification is not subject to the IIA property at the individual consumer level that enables us to distinguish between the effects of IIA violations and the effects of heterogeneity at the aggregate level. At the same time, we account for endogeneity of marketing variables and heterogeneity across consumers. The endogeneity problem arises because of unobserved factors that are firm- and time-period-specific (but invariant across consumers) that could be correlated with exhibitor-title-time-specific marketing-mix variables.

One of the key limitations of the proposed model is that it does not account for competition from the non-exhibitor market, i.e. home-video, rentals, DVD purchases, etc. The model also does not enforce any spatial structure on the competitive interaction between exhibitors in the same geographic market.

While we calibrate our model on movie data, our model and analysis are best suited for product categories in which the choice set available to consumers varies across space and time. Other categories that could potentially be modeled using our demand model include music (physical album sales), hospitality, etc.

In summary, this study has proposed a space- and time-varying choice-set-based aggregate demand model as an alternative to the aggregate logit model that can be used as a basis to investigate competitive interactions among firms in a product market. Using our proposed model, we conduct some counterfactuals to answer important questions pertaining to exhibitors and distributors, i.e. the impact of pricing policy changes and reallocation of the advertising spend between local vs. national advertising. Despite some of its limitations, the results and insights we are able to provide indicate that the proposed specification is a promising alternative to existing methods used for the purpose.

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Appendix: Estimation Algorithm

The parameters of the proposed demand model are consistently estimated using the approach proposed in Berry et al. (1995) using a GMM-based estimator. The estimation algorithm starts by assuming an initial value for the unknown parameters to recover the implied error term which is then interacted with the instruments matrix to form the GMM objective function. The iterative algorithm searches across an expansive space of possible parameters values so as to jointly minimize the value of the objective function computed for the vector of current parameter values.

If Z denote set of instruments such that the population moment conditions are $E(Zp(\boldsymbol{\theta}^*)) = 0$ where $p(\boldsymbol{\theta}^*)$ is the recovered error term, which is a function of model parameters, and $\boldsymbol{\theta}^*$ denote the "true" values of the parameters, then our corresponding GMM estimate is given by:

$$\hat{\theta} = Arg\min_{\theta}\ p(\theta)'Z'\Gamma^{-1}Z'p(\theta) \qquad \text{(A.1)}$$

where Γ^{-1} is the consistent estimate of $E(Z'pp'Z)$.

Decompose the indirect utility into household-invariant and household-varying components $\boldsymbol{\delta}_{jegt}(X^{'}_{jegt}, X^{'}_{egt};\Theta_1)$ and $\boldsymbol{\mu}_{ijegt}(X^{'}_{jegt}, X^{'}_{egt}, D, \upsilon;\Theta_2)$. The estimation procedure involves iterating over two nested loops each, wherein each loop helps recover a subset of the demand-model parameters. In the 'outer' loop, the parameters Θ_2 , i..e. parameters corresponding to the household heterogeneity distribution, and the parameters of the covariance matrix for $\boldsymbol{\varepsilon}$, are computed. The 'inner' loop involves computing the parameters associated with $\boldsymbol{\delta}_{jegt}$.

Step 1: Make r=250 draws for the terms $D_i, \boldsymbol{\upsilon}_i$ for each market *g*. This requires: a) values for heterogeneity variance in D_i, and b) initial guesses for the variance of the unobservable component of heterogeneity $\boldsymbol{\upsilon}_i$ and $\boldsymbol{\varepsilon}$. Note that these constitute the parameters of non-linear components of the indirect utility function. Like Chintagunta (2001), to ensure that the variance matrix of $\boldsymbol{\varepsilon}$ is positive definite, we choose initial values for the Cholesky decomposition of this matrix.

Step 2: Holding the heterogeneity parameters from Step 1 as fixed, we make initial guesses for the $\boldsymbol{\delta}_{jegt}$ terms. We iterate over values of $\boldsymbol{\delta}_{jegt}$ such that with 'fixed' non-linear parameters, we minimize the error between the predicted shares from the random coefficients aggregate logit and the observed market shares. This involves computing the logit shares for each consumer using the iterated value of $\boldsymbol{\delta}_{jegt}$ and the heterogeneity parameters, then averaging the choice probabilities across all *r* consumers to get the market-level, title-specific choice probabilities. That is:

$$s(\boldsymbol{\delta}_{.t};\Theta_2,\Sigma_{\varepsilon}) = S_{.t} \tag{A.2}$$

where

$$\begin{aligned} s(\boldsymbol{\delta}_{.t};\Theta_2,\Sigma_{\varepsilon}) &= \frac{1}{r}\sum_{i=1\ldots r} s_{ijegt} \\ &= \frac{1}{r}\sum_{i=1\ldots r}\left(\frac{\exp(\delta_{jegt}+\boldsymbol{\mu}_{ijegt})}{1+\sum_{k\in J_{gt}}\exp(\delta_{kegt}+\boldsymbol{\mu}_{ikegt})}\right) \end{aligned} \tag{A.3}$$

Step 3: The iteration over $\boldsymbol{\delta}_{.t}$ relies on BLP's contraction mapping procedure, wherein:

$$\delta_{.t}^{h+1} = \delta_{.t}^{h} + \ln(S_{.t}) - \ln(\hat{S}_{.t}) \tag{A.4}$$

such that $\| \boldsymbol{\delta}_{.t}^{h+1} - \boldsymbol{\delta}_{.t}^{h} \| \leq e_{tolerence}$, then $\boldsymbol{\delta}_{.t}^{h} \approx \boldsymbol{\delta}_{.t}$

Step 4: Next, we recover the structural error term as the residual of the recovered $\boldsymbol{\delta}_{.t}$ and $\left(X'_{jegt}\boldsymbol{\beta} + X'_{egt}\boldsymbol{\theta}\right) + \rho\ln(1-\lambda_{jgt})$. This is achieved by estimating the linear parameters using an instrumental variables approach, which allows for the potential correlation between one or more elements in X_{jegt} and the error term.

Step 5: The error term ξ_{jegt} recovered in Step 4 is then interacted with the instrument vector used in Step 4 to provide the GMM objective function as expressed in equation (A.1). Minimizing the objective function forms the basis for recovering the nonlinear parameters, i.e., the heterogeneity parameters. This iterative process forms the 'outer loop'.

Step 6: The corresponding values of $\boldsymbol{\delta}_{.t}$, estimated at the GMM objective-minimizing values of non-linear parameters enables recovery of the linear parameters.

Study	**Time-Varying Consideration Set**	**Title Specific Saturation**	**Retail Competition**
Ainslie et al. (2005)	Yes	No	No
Moul (2005)	No	Yes	No
This Study	Yes	Yes	Yes

Table 1 – Distribution of Cumulative Gross of Top 20 Titles (ranked by Total Cumulative Gross)

Movie	Cumulative Domestic Gross	Share of Total Domestic Box-Office Gross
Shrek 2	$378,495,005.88	5.97
Lord of the Rings: The Return of the King	$339,259,366.61	5.35
Spider-Man 2	$329,884,111.24	5.20
Passion Of The Christ, The	$326,325,217.71	5.15
Harry Potter And The Prisoner Of Azkaban	$214,940,324.63	3.39
Incredibles, The	$205,192,654.45	3.24
Day After Tomorrow, The	$164,456,451.94	2.59
Bourne Supremacy, The	$159,442,699.84	2.51
Elf	$155,117,728.78	2.45
Shark Tale	$140,404,529.28	2.21
I, Robot	$128,841,235.13	2.03
Cheaper By The Dozen (2003)	$125,978,478.59	1.99
Matrix: Revolutions, The	$124,631,397.42	1.97
Troy	$117,559,389.74	1.85
Something's Gotta Give	$117,127,199.49	1.85
50 First Dates	$109,893,615.81	1.73
Van Helsing	$106,366,759.28	1.68
National Treasure	$105,244,337.25	1.66
Fahrenheit 9/11	$104,791,892.53	1.65
Total Revenues (across all movies between November 2003-February 2005)	**$6,341,910,776.97**	
% Share of Total Box-Office Revenues by Top 20 Titles	**54.46**	

Table 2 – Types of Movie Theaters

Types of Theaters	Number of Theaters	Share of Locations
Uniplex	376	11.20048
Miniplex (2 to 7 screens)	1303	38.81442
Multiplex (8 to 15 screens)	1221	36.37176
Megaplex (16+ screens)	457	13.61335
Total	**3357**	

Table 3 – Demographic Variables (209 DMA's)

Market Demographics	Min	Max	Mean
Population	28379.00	15166041.00	2475152.65
%Black	0.00	0.57	0.10
%Hispanic	0.00	0.93	0.13
Income	24741.85	60843.94	45378.94

Table 4 – Reduced-Form Regression Based Variance Decomposition of Daily Exhibitor-level Title-specific Market-Share

Variables	Additional Variance Contribution
Time Since Release (dummies alone)	10.47
DMA Dummies	9.33
Exhibitor Dummies	23.21
Movie Dummies	15.53
DMA Dummies*Time Dummies	6.56
DMA Dummies*Genre Dummies	5.14
Movie Dummies*TimeSinceRelease (single discrete valued covariate)	8.41
Genre Dummies*TimeSinceRelease (single discrete valued covariate)	5.84
Total Variance Explained	**84.49**

Table 5 – List of Variables that Vary by Title

Unit of Analysis	Variable	Explanation	Data source
Title specific Time Invariant Characteristics (X_j)	Genre	Primary and secondary Genre	Data provider
	Rating	Rating grade	Data provider
	Critic Rating	Meta-analysis of critic review across multiple media outlets	Metacritic.com
	Star power	Total number of stars as featured in Variety magazine	Data provider
	Distributor	Identity of distributor for movie	Data provider
	Run Time	Duration of movie (in minutes)	Data provider
Title specific Time Varying Characteristics (X_{jt})	Days since opened National	Days since national release	Data provider
	National-Level Advertising Expenditure	National-level expenditure across channels like Internet, National TV, National Newspapers etc.	TNS Media Intelligence
Title-Market Specific Characteristics (X_{jg})	Opening Day Dummy	=1 if first day since being released in that market. 0 otherwise	Computed
	Opening Weekend Dummy	=1 if first weekend since being released in that market. 0 otherwise.	Computed
Title-Market Specific Characteristics (X_{jgt})	Local-Level Advertising Expenditure	Local-level expenditure across channels like Spot TV, Local Radio, Local Newspapers etc.	TNS Media Intelligence
	Saturation	= log(1-Accumulated Demand in Market/Population of Market) Ref: Moul (2003)	Computed
	Days since released in local market	Time (in days) since the title was first released in local market	Computed
Title-Market-Exhibitor Specific Characteristics (X_{jegt})	Days since released at theater	Time (in days) since the title was first released in the theater	Computed
	Accumulated gross at theater	Cumulative box office at theater from release to previous day	Computed

Table 6 – List of Exhibitor Characteristics

Unit of Analysis	Variable	Explanation	Data source
Exhibitor-Time Invariant Characteristics (X_e)	Number of Screens	Number of physical screens available for screening	Data provider
	Admission Price	Adult ticket price	Collected via web-scraping and calling individual theater locations
	Chain fixed effects	Exhibitor chain affiliation OR Independent	Metacritic.com
	Latitude & Longitude	Geographic coordinates of the theater	Data provider

Table 7 – List of Market Characteristics

Unit of Analysis	Variable	Explanation	Data source
Market-Time Invariant Characteristics (X_g)	Income	Household Income	US Census and Nielsen DMA definitions
	Hispanic	=1 if census respondent is Hispanic	US Census and Nielsen DMA definitions
	Black	=1 if census respondent is Black	US Census and Nielsen DMA definitions
	White	=1 if census respondent is White/Not Black/Hispanic	US Census and Nielsen DMA definitions
	Population	Number of individuals in DMA	US Census and Nielsen DMA definitions
Time specific variables (X_t)	Seasonal effects	Indicator variable for each week	Computed
	Day-of-week effect	Indicator variable for each day of the week	Computed

Table 8: Descriptive Statistics of Estimation Data

Variable	Minimum	Maximum	Mean	Std. Dev
Market share	3.39E-10	7.22E-02	8.71E-05	3.19E-04
Runtime (in minutes)	8.00E+00	2.25E+02	1.09E+02	2.13E+01
Starpower	0.00E+00	6.00E+00	1.96E+00	4.18E-01
Review	3.00E+00	1.00E+02	5.25E+01	1.78E+01
Time Since Start (National)	-3.50E+02	4.42E+02	2.58E+01	2.80E+01
Ln(National Advertising)	-1.15E+01	5.93E+00	-2.24E+00	3.65E+00
Distance from centroid	2.59E-02	2.15E+03	6.49E+00	2.73E+01
Admission price	1.09E+00	1.83E+01	7.41E+00	1.62E+00
Number of screens	1.00E+00	3.00E+01	1.16E+01	5.76E+00
Time Since Start (Theater)	1.00E+00	3.80E+02	2.00E+01	1.86E+01
Accumulated gross at Theater	0.00E+00	1.55E+06	2.50E+04	4.59E+04
Time Since Start (in DMA)	0.00E+00	4.42E+02	2.62E+01	2.65E+01
Saturation	-1.24E+00	-3.39E-10	-2.82E-02	4.32E-02
Ln(Local advertising)	-1.15E+01	5.30E+00	-5.63E+00	4.93E+00
Number of Observations		**12080267**		
Number of markets		**209**		

Table 9 – Distribution of Box-Office Gross across Genres

Genre	Number of Titles	Mean Cumulative Gross	Total Gross	Std. Dev Cumulative Gross
Drama	274	8,733,351.54	2,392,938,322.70	19,992,917.36
Comedy	137	14,551,218.15	1,993,516,887.00	25,028,710.52
Foreign	110	697,578.77	76,733,665.19	3,657,559.42
Documentary	87	1,291,153.62	112,330,365.10	7,146,508.78
Suspense	65	13,838,059.27	899,473,852.43	22,590,195.81
Action	60	30,353,131.32	1,821,187,879.40	37,682,738.84
Adventure	31	48,947,491.23	1,517,372,228.10	50,855,502.78
Gay Interest	31	101,260.02	3,139,060.66	189,365.39
Romance	31	10,133,072.59	314,125,250.21	15,971,093.27
Horror	28	19,038,883.40	533,088,735.14	24,177,955.67
Musical	24	5,108,385.42	122,601,250.06	10,515,527.46
Romantic Comedy	21	21,461,410.37	450,689,617.85	22,946,361.07
Science Fiction	19	38,181,513.84	725,448,762.94	40,671,101.89
Family	17	33,508,684.02	569,647,628.33	40,838,389.17
Animation	16	35,705,292.03	571,284,672.46	49,745,735.21
Crime	16	4,839,574.37	77,433,189.96	9,735,849.35
Urban	14	15,421,980.74	215,907,730.41	12,841,795.04
Sports	13	18,224,093.74	236,913,218.59	23,815,587.49
Biography	11	22,707,163.23	249,778,795.52	47,510,485.67
War	10	4,319,824.65	43,198,246.49	10,574,865.54
Fantasy	7	43,469,153.66	304,284,075.63	54,962,764.59
Religion	6	27,301,040.33	163,806,241.96	64,582,678.74
Mystery	5	19,719,221.26	98,596,106.31	41,119,476.19
Teen	4	25,108,834.12	100,435,336.46	20,042,932.23
CGI	3	73,739,422.01	221,218,266.04	89,018,580.64
Western	3	20,827,638.73	62,482,916.20	21,365,545.64
Historical	2	11,409,015.63	22,818,031.26	15,591,860.19
Martial Arts	2	22,827,802.03	45,655,604.05	31,092,771.35
Unknown	1	4,331.00	4,331.00	

Table 10 – Distribution of Box-Office Gross across Ratings

Rating	Number of Titles	Mean Cumulative Gross	Total Gross	Std. Dev Cumulative Gross
NR	204	129,277.85	26,372,682.24	337,975.20
R	183	9,252,142.36	1,693,142,051.60	19,507,415.83
PG13	116	26,517,669.49	3,076,049,661.10	30,484,871.44
PG	52	27,160,927.39	1,412,368,224.30	37,113,639.11
G	7	18,805,967.22	131,641,770.51	29,441,255.96
NC17	2	1,168,030.96	2,336,061.92	857,583.45

Table 11(a) – Distribution of Box-Office Gross across Top 25 Distributors (ranked by Total Gross)

Distributor	Number of Titles	Mean Cumulative Gross	Total Gross	Std. Dev Cumulative Gross	% Share of Titles	% Share of Total Gross
Sony	24	40,754,000.98	978,096,023.39	34,081,158.48	4.25531915	15.42273
Warner Bros.	24	35,264,193.59	846,340,646.06	30,500,520.40	4.25531915	13.3452
Buena Vista	22	35,982,017.42	791,604,383.28	29,727,409.11	3.90070922	12.48211
20th Century Fox	18	38,969,817.56	701,456,716.03	32,450,526.48	3.19148936	11.06065
Universal	15	40,727,547.47	610,913,212.03	25,237,613.55	2.65957447	9.632952
New Line Cinema	13	37,626,287.44	489,141,736.68	45,265,534.68	2.30496454	7.712845
Paramount	18	25,453,362.23	458,160,520.09	17,769,204.52	3.19148936	7.22433
Dreamworks SKG	8	35,123,209.78	280,985,678.22	57,753,161.30	1.41843972	4.430616
Miramax	17	16,415,658.68	279,066,197.51	19,006,226.10	3.0141844	4.400349
MGM	16	11,769,722.73	188,315,563.74	13,007,909.94	2.83687943	2.969382
Newmarket Film Group	6	30,635,680.71	183,814,084.24	63,585,350.76	1.06382979	2.898402
Lions Gate	17	8,016,684.11	136,283,629.80	11,117,008.39	3.0141844	2.148937
Fox Searchlight	10	11,754,500.04	117,545,000.38	9,127,434.47	1.77304965	1.853464
Focus Features	10	9,806,569.23	98,065,692.28	9,535,920.15	1.77304965	1.546312
Lions Gate/IFC	1	65,594,570.05	65,594,570.05		0.17730496	1.034303
Sony Pictures Classics	22	1,146,546.20	25,224,016.45	1,176,027.20	3.90070922	0.397735
IDP	11	870,172.80	9,571,900.79	1,912,104.97	1.95035461	0.150931
Magnolia Pictures	6	1,327,726.90	7,966,361.39	2,126,342.24	1.06382979	0.125615
Warner Independent Pictures	6	1,225,239.26	7,351,435.54	1,443,364.36	1.06382979	0.115918
Artisan	3	2,429,900.16	7,289,700.47	4,095,764.13	0.53191489	0.114945
Fine Line Features	3	2,402,148.41	7,206,445.23	2,218,182.05	0.53191489	0.113632
ThinkFilm	14	475,181.30	6,652,538.13	771,032.83	2.4822695	0.104898
IFC Films	10	549,901.98	5,499,019.78	951,137.42	1.77304965	0.086709
Televisa Cine	1	3,568,601.14	3,568,601.14		0.17730496	0.05627
New Yorker	10	309,966.49	3,099,664.89	675,096.70	1.77304965	0.048876
Total (Top 25 Distributors by Total Gross)	**295**		**6,305,713,672.70**		**52.30**	**99.43**

Table 11(b) – Distribution of Box-Office Gross across Top 25 Distributors (ranked by Number of Titles)

Distributor	Number of Titles	Mean Cumulative Gross	Total Gross	Std. Dev Cumulative Gross	% Share of Titles	% Share of Total Gross
Sony	24	40,754,000.98	978,096,023.39	34,081,158.48	4.25531915	15.42273
Warner Bros.	24	35,264,193.59	846,340,646.06	30,500,520.40	4.25531915	13.3452
Buena Vista	22	35,982,017.42	791,604,383.28	29,727,409.11	3.90070922	12.48211
Sony Pictures Classics	22	1,146,546.20	25,224,016.45	1,176,027.20	3.90070922	0.397735
20th Century Fox	18	38,969,817.56	701,456,716.03	32,450,526.48	3.19148936	11.06065
Paramount	18	25,453,362.23	458,160,520.09	17,769,204.52	3.19148936	7.22433
Lions Gate	17	8,016,684.11	136,283,629.80	11,117,008.39	3.0141844	2.148937
Miramax	17	16,415,658.68	279,066,197.51	19,006,226.10	3.0141844	4.400349
MGM	16	11,769,722.73	188,315,563.74	13,007,909.94	2.83687943	2.969382
Strand Releasing	16	33,821.29	541,140.60	28,587.69	2.83687943	0.008533
Universal	15	40,727,547.47	610,913,212.03	25,237,613.55	2.65957447	9.632952
ThinkFilm	14	475,181.30	6,652,538.13	771,032.83	2.4822695	0.104898
New Line Cinema	13	37,626,287.44	489,141,736.68	45,265,534.68	2.30496454	7.712845
Palm Pictures	12	73,404.27	880,851.27	62,712.06	2.12765957	0.013889
IDP	11	870,172.80	9,571,900.79	1,912,104.97	1.95035461	0.150931
First Run	10	32,621.43	326,214.30	32,444.96	1.77304965	0.005144
Focus Features	10	9,806,569.23	98,065,692.28	9,535,920.15	1.77304965	1.546312
Fox Searchlight	10	11,754,500.04	117,545,000.38	9,127,434.47	1.77304965	1.853464
IFC Films	10	549,901.98	5,499,019.78	951,137.42	1.77304965	0.086709
New Yorker	10	309,966.49	3,099,664.89	675,096.70	1.77304965	0.048876
Wellspring Media	10	158,115.98	1,581,159.78	187,903.17	1.77304965	0.024932
Dreamworks SKG	8	35,123,209.78	280,985,678.22	57,753,161.30	1.41843972	4.430616
Innovation Film Group	8	61,982.24	495,857.89	87,558.77	1.41843972	0.007819
TLA Releasing	8	111,575.71	892,605.66	245,783.11	1.41843972	0.014075
Paramount Classics	7	351,143.82	2,458,006.76	151,275.26	1.24113475	0.038758
Total (Top 25 Distributors by Number of Titles)	**350**		**6,033,197,975.79**		**62.0567376**	**95.13218**

Table 12 – Parameter Estimates of Title-Specific Time Invariant Characteristics (Mean Estimates)

Sub-Category	Variable	Aggregate Logit (Demand Model)							
		Mean Effect (Mean Differenced)		Income		Black		Hispanic	
		Estimate	tValue	Estimate	tValue	Estimate	tValue	Estimate	tValue
	Runtime (in minutes)	2.40E-03	86.28	-6.62E-08	-17.31	1.54E-09	16.54	-3.44E-10	-15.15
	Starpower	1.47E-01	116.57	4.03E-07	2.36	-2.44E-08	-5.81	-3.98E-09	-3.91
	Critic Review	1.09E-02	382.00	2.05E-07	52.27	-1.27E-09	-13.20	-2.50E-10	-10.85
Rating (Base= NC17)	NR	-2.48E-01	-28.96	-5.82E-06	-3.11	-1.49E-08	-0.39	1.24E-08	1.30
	R	-4.23E-01	-46.69	-3.80E-06	-1.98	-1.84E-07	-4.60	1.09E-08	1.10
	PG13	-2.64E-01	-30.63	-8.84E-06	-4.72	-2.06E-08	-0.53	-3.08E-09	-0.32
	PG	-2.56E-01	-29.47	-8.16E-06	-4.34	-4.01E-08	-1.03	-1.29E-08	-1.34
	G	1.51E-01	16.71	-1.19E-05	-6.23	7.42E-08	1.86	-5.06E-08	-5.12
Genre (Base= Others)	Drama	3.61E-02	32.89	4.42E-06	29.03	-2.92E-08	-7.83	1.22E-08	13.40
	Foreign	-4.68E-02	-10.86	3.78E-06	7.74	4.94E-08	4.70	3.11E-09	1.23
	Comedy	-8.95E-03	-7.60	2.68E-06	16.44	-2.67E-09	-0.67	-4.49E-09	-4.63
	Documentary	6.45E-01	135.20	-4.88E-06	-8.38	-1.40E-07	-10.45	-5.48E-08	-16.58
	Suspense	-1.33E-01	-108.54	-7.29E-07	-4.28	8.48E-09	2.04	-1.14E-08	-11.24
	Action	-1.84E-01	-153.67	2.53E-06	15.32	-4.60E-08	-11.39	1.47E-08	14.97
	Romance	-1.67E-01	-98.36	2.71E-06	11.63	-7.99E-08	-14.22	9.74E-09	7.11
	Adventure	9.57E-03	6.12	-3.18E-06	-14.55	6.73E-08	12.44	-1.23E-08	-9.37
	Gay Interest	6.38E-02	47.19	-1.82E-06	-9.60	-1.10E-08	-2.34	1.37E-09	1.19
	Horror	-1.19E-01	-5.66	-1.17E-05	-5.93	3.96E-07	11.05	-6.60E-08	-8.40
Distributor (Base= Others)	Sony	-7.64E-01	-21.22	2.85E-05	7.50	-7.72E-07	-12.28	1.50E-07	10.72
	Warner Bros.	2.64E-01	145.87	-1.31E-06	-5.32	-1.68E-08	-2.83	-1.06E-08	-7.41
	Buena Vista	2.74E-01	141.96	2.20E-07	0.83	-1.11E-07	-17.00	-9.55E-10	-0.60
	Sony Pictures Classics	-2.34E-01	-31.78	1.06E-05	14.37	1.63E-07	10.56	2.78E-08	7.33
	20th Century Fox	2.67E-01	144.50	-7.79E-06	-30.46	1.59E-08	2.56	-6.07E-10	-0.40
	Paramount	3.87E-03	2.04	-8.52E-07	-3.25	-1.03E-07	-16.16	1.35E-08	8.60
	Lions Gate	1.18E-01	56.39	-5.63E-06	-20.19	6.83E-08	10.30	-1.73E-08	-10.79
	Miramax	6.14E-02	22.32	-5.64E-06	-15.19	1.22E-07	13.69	-1.31E-08	-6.11
	MGM	5.96E-01	11.56	-5.08E-05	-12.66	5.55E-07	8.22	-1.15E-07	-7.75
	Strand Releasing	1.84E-01	91.60	-2.84E-06	-10.33	-1.62E-08	-2.43	-4.34E-09	-2.70
National Release	Opening Weekend Dummy (National)	6.37E-01	284.57	8.50E-06	29.75	-4.73E-08	-7.33	4.67E-08	28.26
	Opening Day Dummy (National)	5.03E-01	122.92	1.97E-06	3.86	-2.00E-08	-1.77	1.49E-08	5.10

Table 13 – Full Model Parameter Estimates for X_{jt} , X_{jg} , X_{jgt} , X_{jegt} and X_e (Heterogeneity Estimates) (cont'd)

Category	Variable	Aggregate Logit (Demand Model)							
		Mean Effect (Mean Differenced)		Income		Black		Hispanic	
		Estimate	tValue	Estimate	tValue	Estimate	tValue	Estimate	tValue
Title specific Time Varying Characteristics (Xjt)	Time since National Release (in days)	-4.38E-03	-122.86	2.54E-07	52.71	-4.67E-09	-41.74	-2.55E-10	-9.63
	Log(National Advertising)	3.04E-02	137.77	1.56E-07	5.51	8.51E-10	1.24	3.73E-09	25.53
Title-Market Specific Characteristics (Xjg)	Opening Weekend Dummy (Market)	9.54E-03	4.19	-4.42E-06	-14.97	-2.39E-08	-3.45	-3.10E-08	-17.32
	Opening Day Dummy (Market)	-1.88E-01	-45.13	-2.98E-06	-5.51	1.72E-08	1.33	-2.01E-08	-6.03
Title-Market Specific Time Varying Characteristics (Xjgt)	Time since release in market (in days)	-2.26E-03	-60.33	-2.14E-07	-42.25	1.72E-09	15.07	3.46E-10	13.30
	Title-specific Saturation	9.26E-01	64.96	7.11E-05	39.19	5.23E-08	1.15	1.32E-07	11.93
	Log(Local Advertising)	8.17E-03	62.55	-4.83E-08	-2.40	4.72E-09	7.67	4.81E-09	29.70
Title-Market-Exhibitor Specific Characteristics (Xjegt)	Time since release in theater (in days)	-1.65E-02	-670.65	-6.48E-08	-4.52	6.68E-03	19.40	-3.10E-03	-25.32
	Accumulated gross in theater	6.44E-06	521.17	1.01E-10	11.29	4.00E-12	23.27	-1.24E-12	-38.14
Exhibitor-Time Invariant Characteristics (Xe)	Chain 1	3.22E-01	94.08	-2.49E-06	-3.24	3.60E-08	1.33	1.12E-07	6.72
	Chain 2	8.42E-02	24.12	9.11E-07	1.15	5.94E-08	2.13	-3.12E-07	-17.00
	Chain 3	3.96E-01	94.56	-8.49E-07	-1.06	1.36E-07	4.96	1.19E-07	7.10
	Chain 4	2.76E-01	75.33	-1.88E-06	-2.39	2.60E-07	9.53	8.41E-08	5.06
	Chain 5	2.39E-01	66.91	9.01E-07	1.11	-6.49E-08	-2.28	5.95E-08	3.57
	Chain 6	3.13E-01	66.07	3.66E-06	4.32	-2.43E-07	-8.69	2.27E-07	13.47
	Chain 7	-1.28E-01	-26.49	-5.37E-06	-6.12	6.06E-07	17.63	-7.86E-08	-3.39
	Chain 8	3.61E-01	63.11	-6.94E-06	-7.27	1.68E-07	3.27	1.56E-08	0.46
	Chain 9	1.72E-01	36.76	5.39E-06	6.34	2.21E-07	5.73	5.87E-08	3.45
	Chain 10	2.58E-01	54.26	1.75E-05	17.34	-9.85E-07	-29.94	1.83E-07	9.50
	Distance from market centroid	-8.08E-04	-9.97	2.40E-09	0.34	-7.96E-09	-37.29	9.40E-10	29.37
	Admission Price	-1.62E-01	-611.73	-1.25E-07	-3.59	-7.34E-09	-9.99	8.42E-09	48.58
	No. of Screens	6.86E-02	771.99	-1.43E-06	-121.77	-1.82E-08	-62.93	-1.22E-09	-21.05

Table 14: Predictor Variables used in the National-Level Demand Model

Classification	Variable
Title-Specific Time Invariant Characteristics (X_j)	Genre
	Rating
	Critic Rating
	Star power
	Run Time
	Opening Day Dummy[14]
	Opening Weekend Dummy[15]
Title-Specific Time Varying Characteristics (X_{jt})	Time since national release (days)
	Number of theater locations
	National-Level Advertising Expenditure
	Local-Level Advertising Expenditure[16]
	Saturation[17]

[14] =1 if first day since being released nationally. 0 otherwise. Note, that in the exhibitor-level model this variable was operationalized as =1 if first day since being released in that market. 0 otherwise.

[15] =1 if first weekend since being released nationally. 0 otherwise. Note, that in the exhibitor-level model this variable was operationalized as =1 if first weekend since being released in that market. 0 otherwise.

[16] Local advertising spends were aggregated upto the national-level and included in the national-level model as a separate predictor variable.

[17] Note, in the exhibitor-level model *Saturation* was measured as *log(1-Accumulated Demand in Market/Population of Market)* Ref: Moul (2003). In the national-level model this is operationalized as *log(1-Accumulated National Demand/National Population).*

Table 15 – Parameter Estimates of Ainslie et al. Model

Sub-Category	Variable	Estimate	t-value
	Starpower	-1.61E-02	-8.43
	Critic Review	1.10E-02	258.02
	Runtime (in minutes)	5.43E-03	132.44
Rating (Base=NC17)	NR	-1.59E-01	-12.23
	R	-2.43E-01	-18.42
	PG13	-9.10E-02	-7.00
	PG	5.76E-01	41.23
	G	-4.21E-01	-13.74
Genre (Base=Others)	Drama	-2.33E-02	-11.60
	Foreign	-7.43E-03	-3.64
	Comedy	-2.15E-01	-36.20
	Documentary	2.34E-01	34.15
	Suspense	-1.05E-01	-56.83
	Action	-1.10E-01	-61.90
	Romance	7.36E-02	36.00
	Adventure	-2.14E-01	-86.04
	Gay Interest	-2.46E-02	-0.78
	Horror	4.46E-02	19.80
Distributor (Base=Others)	Sony	6.95E-01	21.74
	Warner Bros.	6.26E-01	19.01
	Buena Vista	2.68E-02	0.65
	Sony Pictures Classics	7.16E-01	22.83
	20th Century Fox	6.68E-01	21.41
	Paramount	5.04E-01	14.84
	Lions Gate	7.65E-01	19.95
	Miramax	1.17E-01	3.12
	MGM	4.36E-01	4.83
	Strand Releasing	5.19E-01	12.32
	Universal	8.37E-01	23.62
	ThinkFilm	5.96E-01	9.65
	New Line Cinema	6.80E-01	17.67
Title specific Time Varying Characteristics (Xjt)	Time since National Release (in days)	-6.04E-04	-2.98
	Number of theater locations	5.28E-03	23.65
	Ln(National Advertising)	6.56E-02	45.59
	Ln(Total Local Advertising)	2.41E-01	149.81
	Title-specific Saturation	-7.22E+01	-126.91
	Opening Weekend Dummy (National)	2.64E+00	126.43
	Opening Day Dummy (National)	5.90E-01	13.43

Table 16: In-sample and Out-of-sample fit and comparison with model that used aggregated data

	Proposed Model	Aggregate Model
In-sample MAPE		
Daily share prediction	19.44%	36.45%
Cumulative share prediction	16.29%	31.69%
Out-of-sample MAPE		
Daily share prediction	23.17%	42.90%
Cumulative share prediction	19.03%	34.44%

Table 17: Theater-level Price Change Counterfactual (percentage change in market shares)

Atlanta, GA					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 2**	**Location 3, Chain 3**	**Location 4, Chain 1**	**Location 5, Chain 5**
Location 1, Chain 1	-3.89	1.48	2.00	0.63	0.80
Location 2, Chain 2	1.32	-3.71	0.69	0.85	1.56
Location 3, Chain 3	0.77	0.93	-1.28	0.88	0.40
Location 4, Chain 1	0.63	1.85	0.57	0.15	0.97
Location 5, Chain 5	0.39	0.28	1.35	0.93	-1.10
Dallas, TX					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 2**	**Location 3, Chain 3**	**Location 4, Chain 4**	**Location 5, Chain 5**
Location 1, Chain 1	-3.75	2.38	2.32	1.29	1.59
Location 2, Chain 2	1.34	-2.84	1.50	1.18	1.77
Location 3, Chain 3	1.68	1.59	-0.82	1.46	0.52
Location 4, Chain 4	1.46	2.48	1.05	0.28	1.51
Location 5, Chain 5	0.45	1.27	1.98	1.71	-0.50
Seattle, WA					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 1**	**Location 3, Chain 2**	**Location 4, Chain 3**	**Location 5, Chain 4**
Location 1, Chain 1	-2.76	2.68	3.12	2.16	2.26
Location 2, Chain 1	1.57	-2.29	1.83	1.89	2.15
Location 3, Chain 2	2.07	2.48	-0.59	2.37	0.66
Location 4, Chain 3	2.35	2.89	1.18	0.68	2.21
Location 5, Chain 4	0.48	2.22	2.77	2.68	-0.37

Note: Effect of a one dollar price increase (row) on the percentage change in share (column)

Table 18: Exhibitor chain-level Price Change Counterfactual (percentage change in market shares)

Atlanta, GA					
Chain	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	**Chain 5**
Chain 1	-9.44	2.13	2.69	1.22	2.58
Chain 2	1.74	-3.84	2.42	1.20	3.18
Chain 3	2.88	3.28	-9.46	3.43	2.57
Chain 4	2.77	0.70	3.47	-10.66	1.31
Chain 5	2.90	1.31	1.66	1.72	-5.73
Dallas, TX					
Chain	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	**Chain 5**
Chain 1	-6.68	1.78	2.31	1.65	2.48
Chain 2	1.62	-2.51	2.42	1.82	2.28
Chain 3	2.81	2.40	-6.09	3.44	2.17
Chain 4	2.21	1.41	2.87	-6.74	1.67
Chain 5	2.29	1.91	1.92	1.84	-3.11
Seattle, WA					
Chain	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	**Chain 5**
Chain 1	-4.62	1.87	1.85	1.19	2.60
Chain 2	2.07	-1.08	1.96	1.76	1.92
Chain 3	2.08	2.34	-3.84	2.71	1.56
Chain 4	2.21	1.50	2.33	-4.25	1.90
Chain 5	1.82	2.06	1.50	1.51	-2.08

Note: Effect of a one dollar price increase (row) on the percentage change in share (column)

Table 19: Counterfactual Results when All National-level Advertising Spend are proportionally allocated to Local-Advertising Spend i.e. ALL LOCAL ADVERTISING (percentage change in market shares)

Atlanta, GA					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-3.33	0.91	3.78	0.36	2.42
Distributor 2	4.14	-0.99	3.16	5.48	1.22
Distributor 3	0.97	0.56	-2.00	3.44	1.84
Distributor 4	0.97	4.53	1.42	-1.24	1.29
Distributor 5	3.81	1.84	5.08	0.77	-5.03
Dallas, TX					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-8.64	1.06	6.79	0.66	4.09
Distributor 2	8.28	-3.67	6.39	11.42	1.44
Distributor 3	2.62	2.67	-5.83	7.13	4.51
Distributor 4	1.45	7.20	3.45	-3.51	3.11
Distributor 5	7.99	4.27	11.94	1.53	-12.16
Seattle, WA					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-4.25	0.53	3.19	0.54	2.32
Distributor 2	2.95	-0.97	3.99	4.98	1.08
Distributor 3	1.17	0.51	-3.11	3.37	2.22
Distributor 4	0.16	2.98	1.01	-2.25	1.53
Distributor 5	3.66	1.70	4.32	1.53	-5.73

Note: Effect of ALL LOCAL Advertising (row) on the percentage change in share (column)

Table 20: Counterfactual Results when All National-level Advertising Spend are proportionally allocated to Local-Advertising Spend i.e. ALL LOCAL ADVERTISING (percentage change in market shares)

Atlanta, GA					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-2.59	1.71	3.99	1.17	2.67
Distributor 2	4.30	-0.66	4.03	5.84	1.80
Distributor 3	1.15	0.77	-1.54	4.19	2.29
Distributor 4	1.33	5.42	2.10	-1.01	2.14
Distributor 5	4.11	2.65	5.72	1.56	-5.00
Dallas, TX					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-7.98	1.66	7.46	0.79	4.67
Distributor 2	8.31	-3.56	6.70	11.99	2.10
Distributor 3	2.75	3.33	-5.55	7.66	4.90
Distributor 4	1.71	8.14	3.61	-3.38	3.60
Distributor 5	8.22	4.44	12.67	1.76	-11.41
Seattle, WA					
Distributor	**Distributor 1**	**Distributor 2**	**Distributor 3**	**Distributor 4**	**Distributor 5**
Distributor 1	-3.39	0.86	3.28	1.06	3.05
Distributor 2	3.89	-0.74	4.07	5.96	1.13
Distributor 3	1.94	1.22	-2.48	3.83	2.99
Distributor 4	0.89	3.58	1.94	-1.74	2.49
Distributor 5	4.19	2.51	4.33	1.66	-5.62

Note: Effect of ALL NATIONAL Advertising (row) on the percentage change in share (column)

Table 21: Counterfactual Results when WORST PERFORMING TITLE is replaced (percentage change in market shares)

Atlanta, GA					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 2**	**Location 3, Chain 3**	**Location 4, Chain 1**	**Location 5, Chain 5**
Location 1, Chain 1	0.60	0.36	0.60	0.04	0.24
Location 2, Chain 2	0.89	0.79	0.47	1.32	1.74
Location 3, Chain 3	-0.38	-0.41	0.40	-0.22	0.14
Location 4, Chain 1	0.17	0.52	0.59	-0.09	0.16
Location 5, Chain 5	1.01	0.36	-0.86	-0.50	-0.58
Dallas, TX					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 2**	**Location 3, Chain 3**	**Location 4, Chain 4**	**Location 5, Chain 5**
Location 1, Chain 1	0.02	1.24	0.17	-0.64	0.40
Location 2, Chain 2	0.48	0.92	0.81	0.24	0.23
Location 3, Chain 3	1.00	-0.96	0.37	0.97	1.07
Location 4, Chain 4	0.12	-0.16	0.17	0.15	-0.91
Location 5, Chain 5	-0.23	0.22	0.20	0.34	0.71
Seattle, WA					
Exhibitor	**Location 1, Chain 1**	**Location 2, Chain 1**	**Location 3, Chain 2**	**Location 4, Chain 3**	**Location 5, Chain 4**
Location 1, Chain 1	1.29	0.12	0.22	0.02	1.10
Location 2, Chain 1	1.26	0.02	-0.07	0.77	0.46
Location 3, Chain 2	1.16	0.30	1.42	0.93	-0.02
Location 4, Chain 3	0.94	0.99	0.57	-0.48	0.85
Location 5, Chain 4	-0.71	-0.32	0.34	0.53	0.51

Note: Effect of dropping worst performing title (row) on the percentage change in share (column)

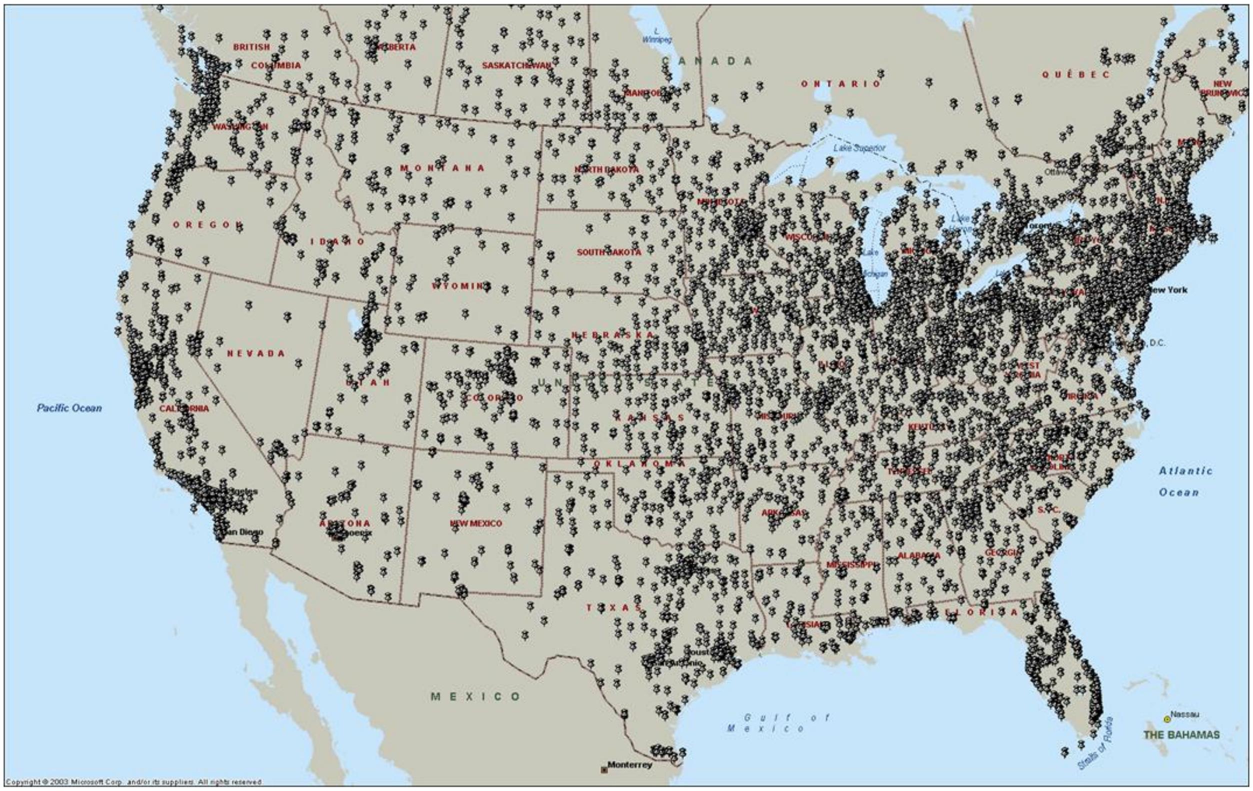


Figure 1: Exhibitor Locations (USA & Canada)

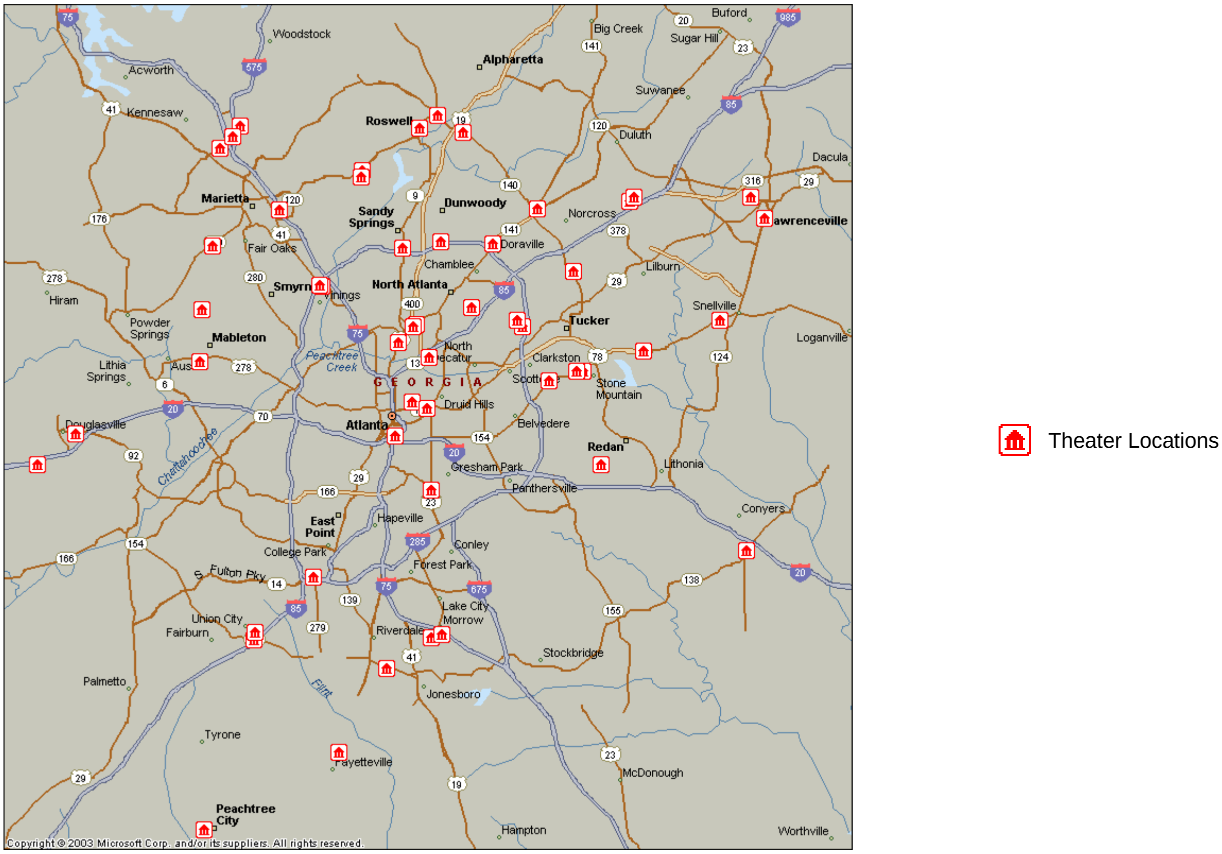


Figure 2: Exhibitor Locations in Atlanta, GA

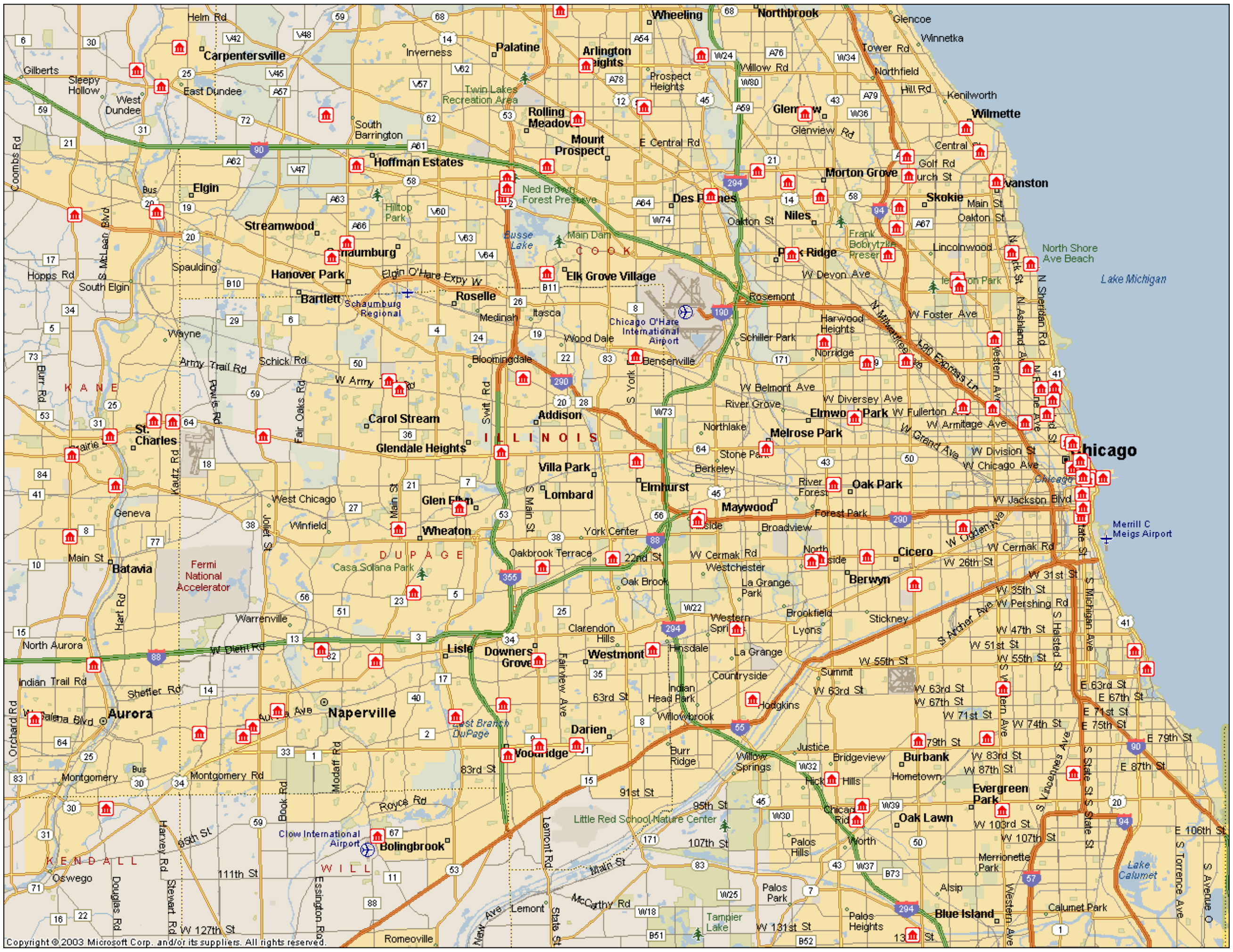
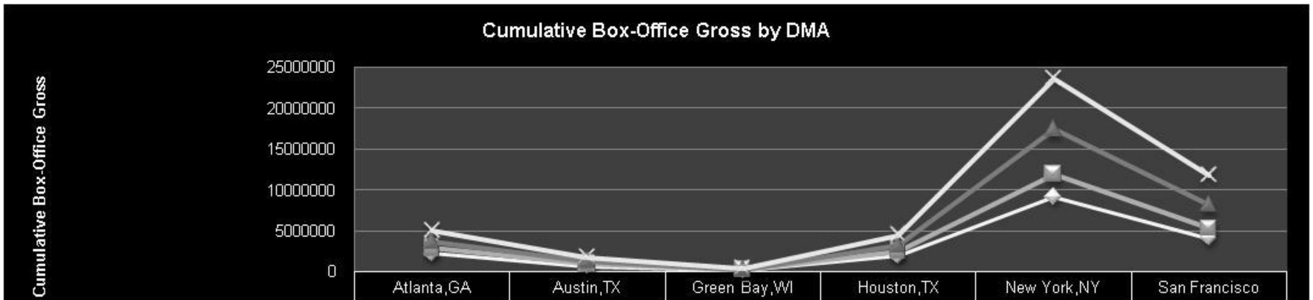
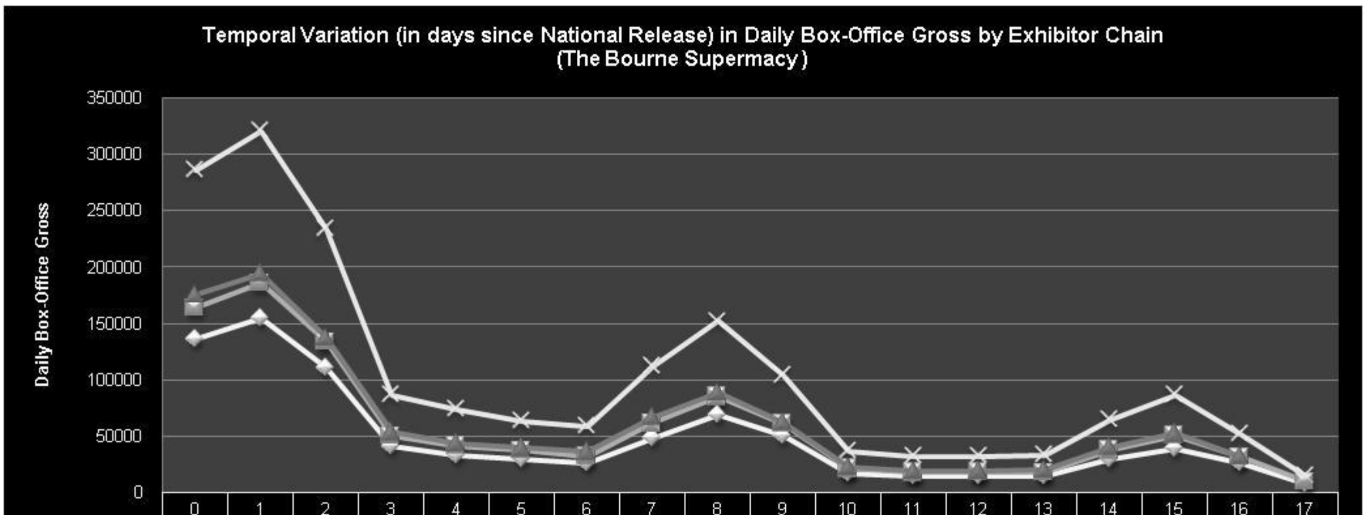


Figure 3: Exhibitor Locations in Chicago, IL



	Atlanta,GA	Austin,TX	Green Bay,WI	Houston,TX	New York,NY	San Francisco
Last Samurai, The	1271927.35	439798.74	122111.12	1231047.02	6234598.27	3611155.75
Kill Bill Vol. 1	888753.46	385335.55	56499.57	783439.1	5478390.22	2934503.82
Bridget Jones: The Edge Of Reason	662435.59	258789.17	46001	593612.25	2770939.11	1199290.75
Bourne Supremacy, The	2196545.56	659133.75	179479.54	1909134.57	9144190.46	4087322.75

Figure 4 – Cross-Sectional Variation in Select Titles across Select DMAs (Cumulative Box Office Revenues)



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Chain D	111116	126760	97210	33741	30761	24703	23296	45334	64129	41865	14883	13526	13287	13673	24470	34639	20689	5592
Chain C	11614	8340	3498	2900	2639	2012	3982	5633	3623	1342	1486	1587	1269	2330	3114	1676	384	
Chain B	27695	31523	22952	9220.8	8285.5	7322	5895.5	12653	15491	10851	3967.5	2952.5	3238.5	3220.5	7552.5	10871	5611	1598.5
Chain A	135691	153985	110288	40978	32743	29844	26033	48489	68957	49884	16860	14304	14849	14381	29483	39344	25797	7807

Figure 5 – Cross-Sectional Variation in Cumulative Box office Revenues for The Bourne Supremacy within DMA across Exhibitor Chains (within Atlanta DMA)

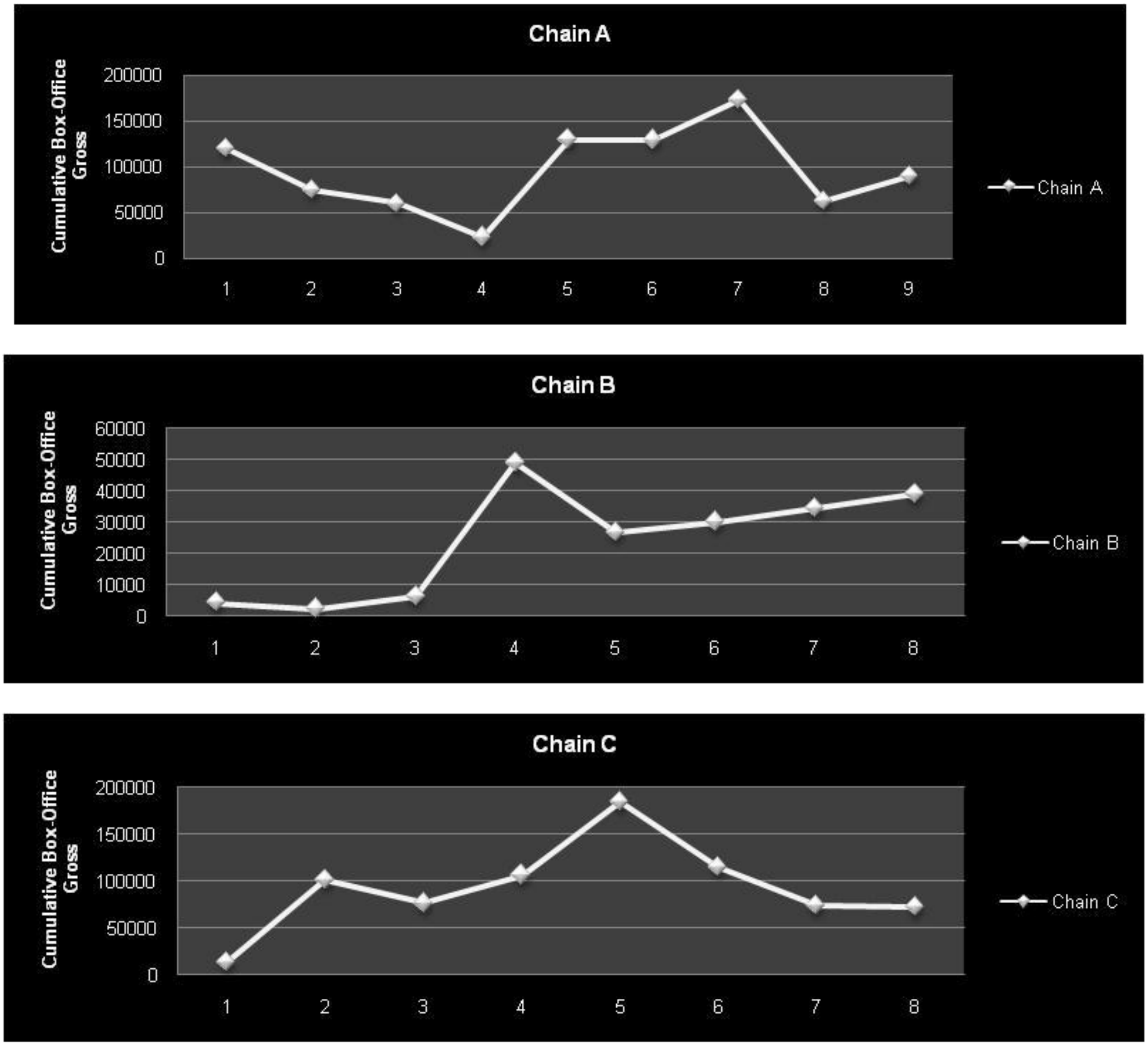


Figure 6 – Cumulative Box-Office Gross vary within a DMA by Chain and within Chain by Location (Example - The Bourne Supremacy)

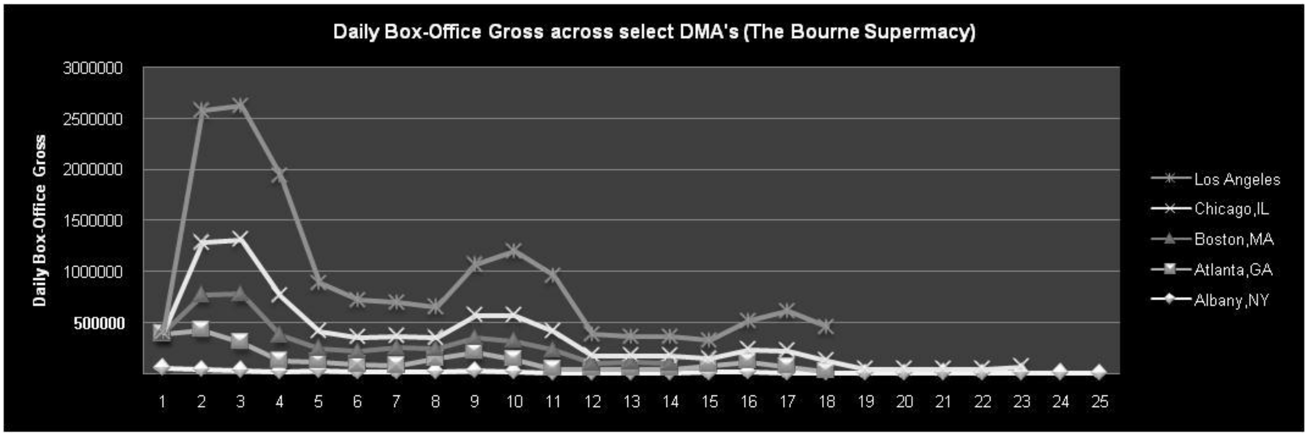
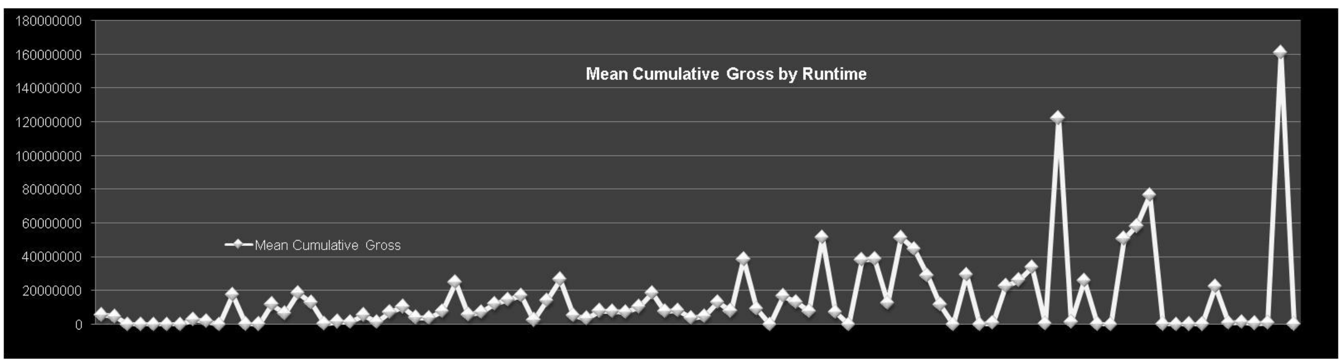
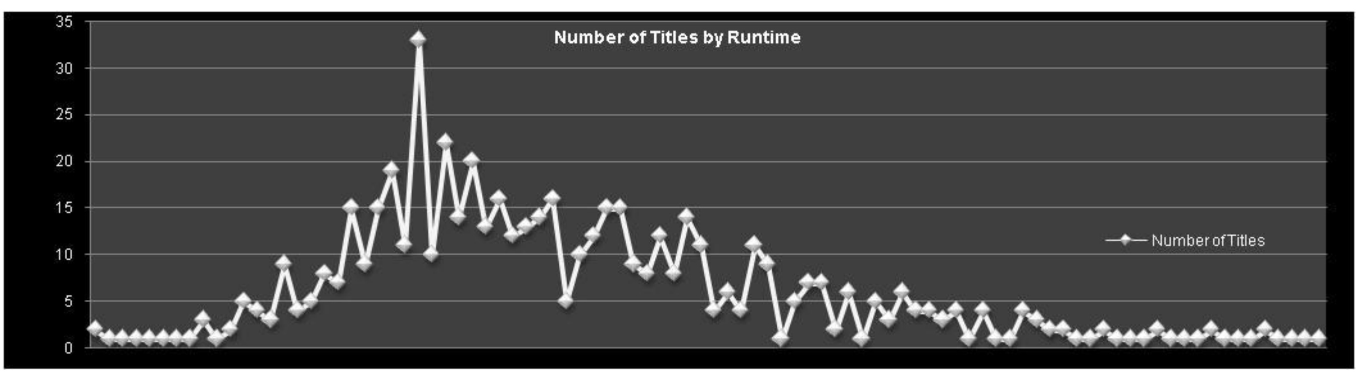


Figure 7 – Temporal Variation in Daily Title-specific Box-Office across DMA's (Example - The Bourne Supremacy)



X axis: Runtime (in mins)   Y axis: Mean Cumulative Gross



X axis: Runtime (in mins)   Y axis: Number of Titles

Figure 8 – Distribution of Share of Box-Office Gross by Runtime (in minutes)

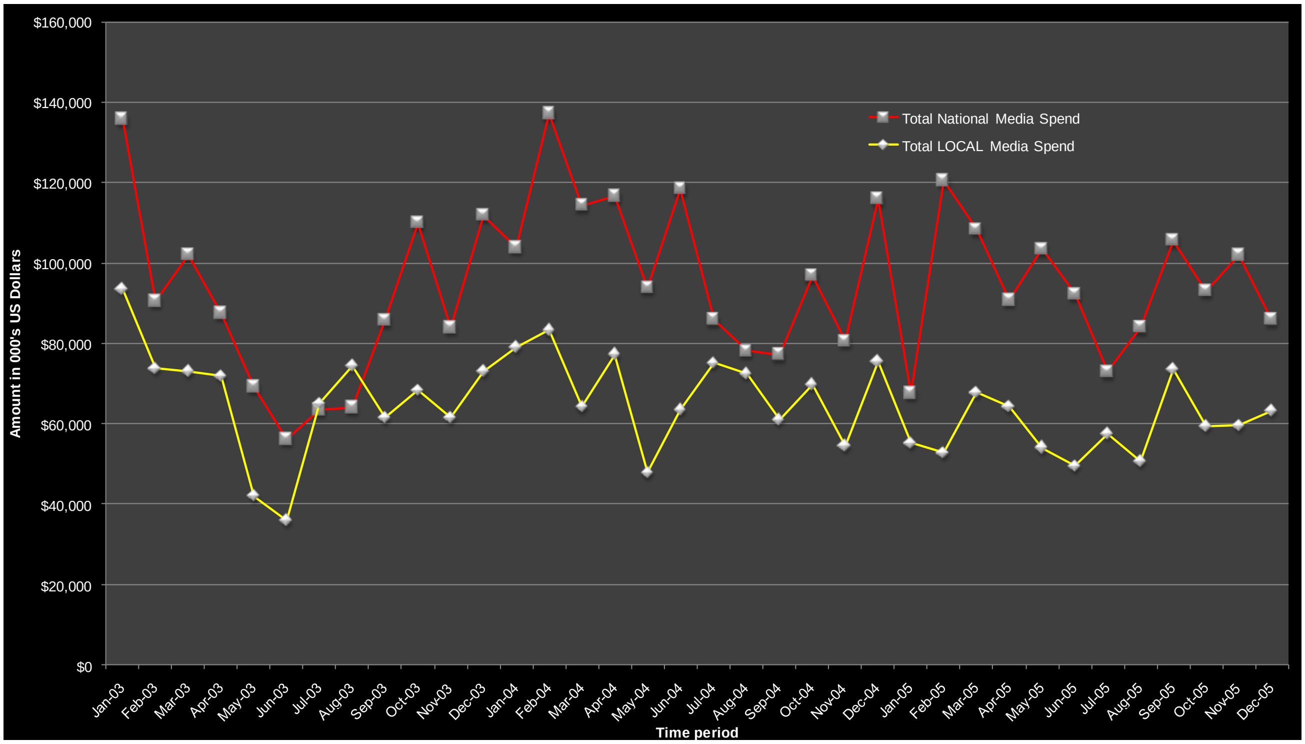


Figure 9 – Aggregate National and Local Advertising Time Series

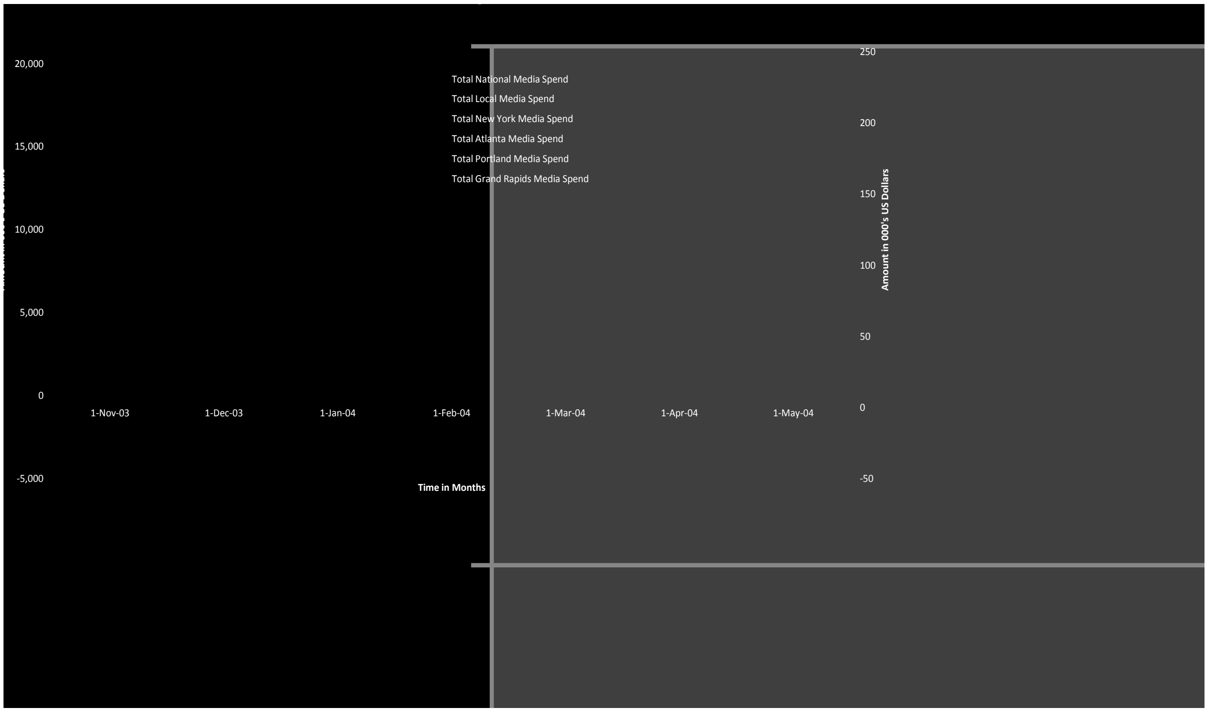


Figure 10 – Cross-Sectional and Temporal Heterogeneity in National and Local Advertising Time Series for <u>The Lord of the Rings 2</u>

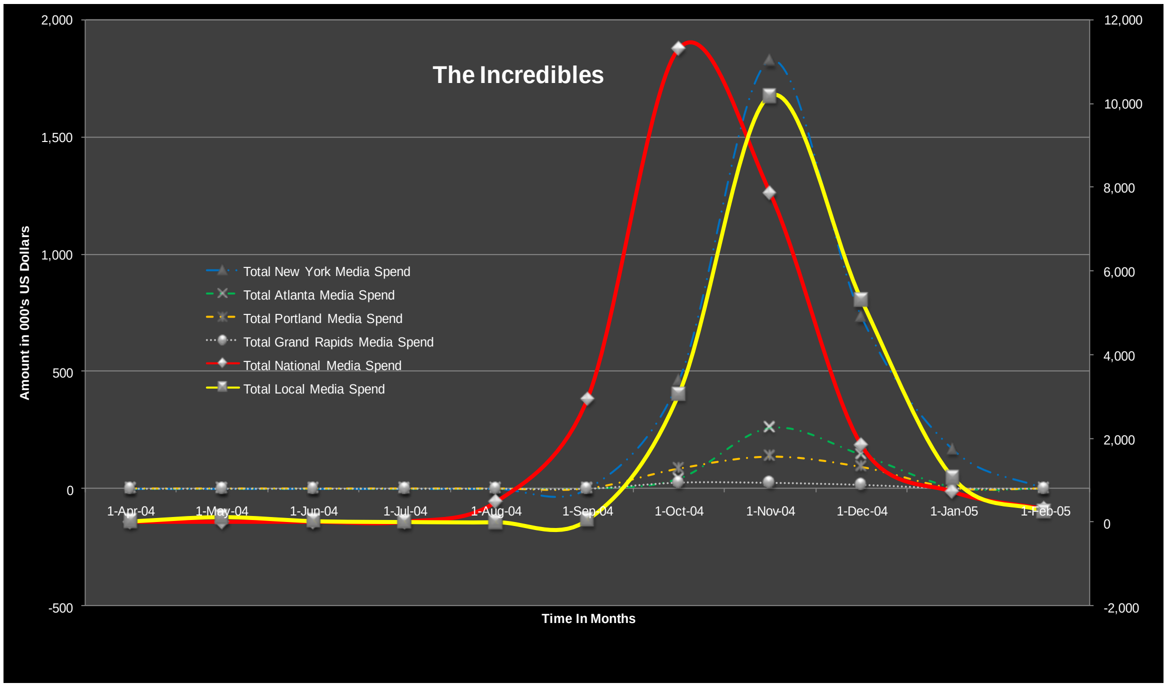
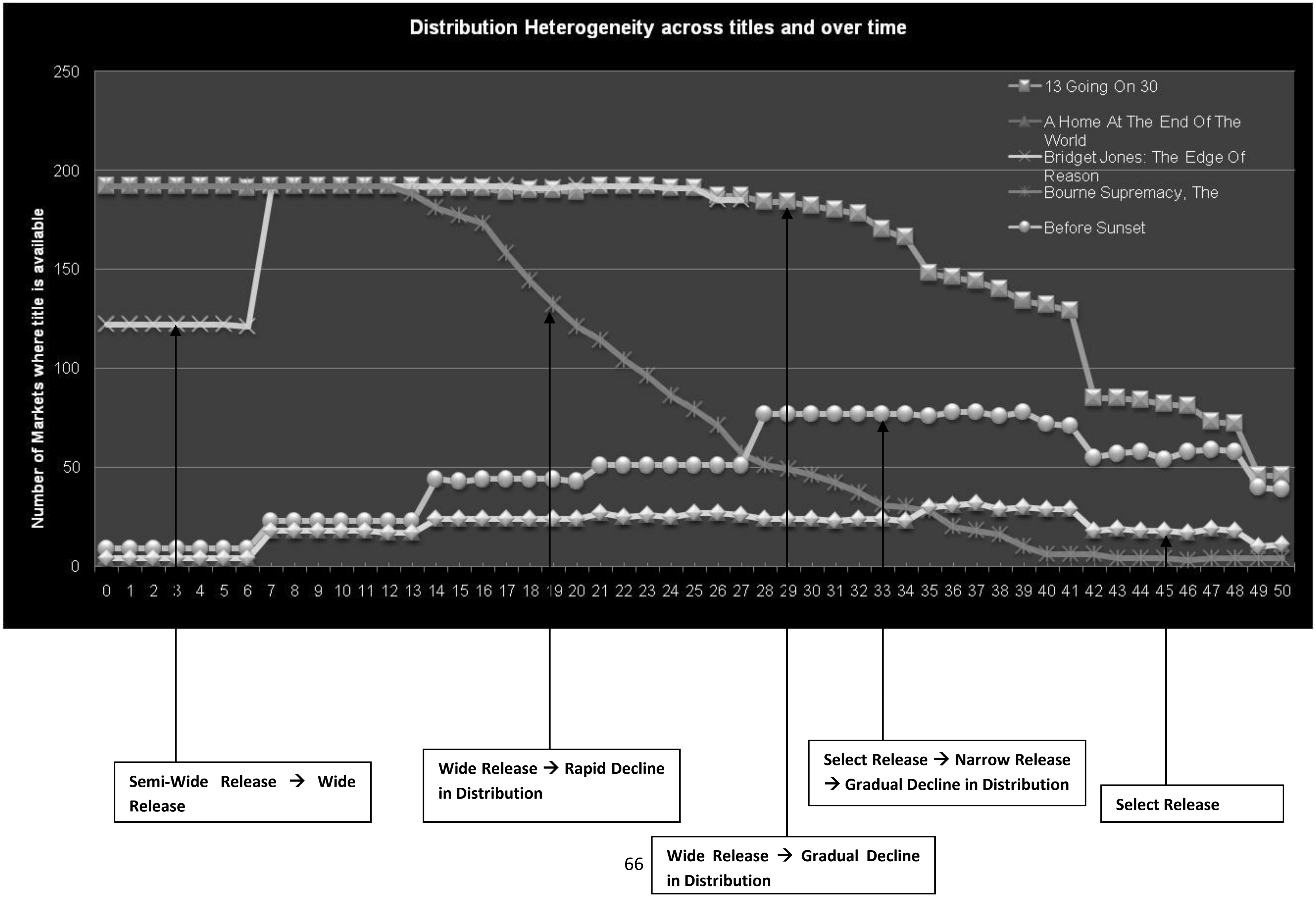


Figure 11 – Cross-Sectional and Temporal Heterogeneity in National and Local Advertising Time Series for <u>The Incredibles</u>


Distribution Heterogeneity across titles and over time
Number of Markets where title is available
13 Going On 30
A Home At The End Of The World
Bridget Jones: The Edge Of Reason
Bourne Supremacy, The
Before Sunset
Semi-Wide Release → Wide Release
Wide Release → Rapid Decline in Distribution
Wide Release → Gradual Decline in Distribution
Select Release → Narrow Release → Gradual Decline in Distribution
Select Release