Spatial Competition in Retail Markets: Movie Theaters.*

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Abstract

Retail markets are extremely important, but economists have few practical tools for analyzing the way dispersed buyers and sellers affect the properties of markets. In this paper, I develop an econometric model of retail demand, a model in which products are location specific and consumers have preferences over both geographic and other product characteristics. I show how to incorporate data on the geographic and demographic distribution of consumers *within* a market into the model. Using data from movie theaters, I evaluate the effect of choices about theater characteristics (price and quality) on rivals. I find that the business stealing effects across theaters are small and significantly decrease with distance. Next I use theater cost data to estimate an hedonic theater cost function. I combine the demand and supply models to consider the retailer's optimal store scale decision. The estimates suggest that the market may substantially *under*-provide movie screens relative to the socially optimal size of movie theaters because the model estimates imply that theaters are frequently close to being local monopolists.

Key Words: Spatial differentiation; Retail markets ; Local market power; Store scale choice; Optimal product provision.
JEL Classification: L0; L1; L2 ; L4.

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1 Introduction

"[B]ecause, once in place, most multi-screen theaters in new markets effectively satisfy market demand, the Company has no competition in over 67% of its theater locations."[1]

Retail markets constitute 30% of the United States economy, employ 18.5 million people and provide the interface between consumers and producers for vast numbers of products. As the final stage in the distribution channel, retail markets are also inherently differentiated product markets, so retailers may benefit from market power. If so, researchers since Hotelling (1929) have established that the resulting differences in social and private incentives can potentially translate into substantially sub-optimal location, scale or pricing decisions. Quotations such as the one above are not entirely reassuring.

Familiar theoretical constructions such as the linear or circular city, developed by Hotelling (1929) and Salop (1979) respectively, are extensively used to study the potential for market power theoretically. Spence (1976) outlines the fundamental economic forces at work and explores their implications for the types and number of products provided by the market: On the one hand, private companies do not consider the reduction imposed on rivals' revenues when they take actions like building additional capacity. This business stealing or cannibalization effect can result, for instance, in the excessive market provision of products. On the other hand, firms are unlikely to be able to capture all of the benefits from introducing new products. This un-captured consumer-surplus effect can, to continue the for instance, result in the private provision of too few products.

Which of these two counterbalancing forces dominates has been shown to depend on detailed features of the competitive environment such as the form of the distribution of consumers (see Eaton and Lipsey (1975) and Spence (1976) among others) and the nature of transport costs (see d'Aspremont, Gabszewicz, and Thisse (1979), who characterize equilibrium for the quadratic transport case and demonstrate that has features that are substantially different from those proposed by Hotelling (1929) for the linear case. See also the recent results in Ansari, Economides, and Steckel (1998) and Irmen and Thisse (1998).)

The aim of this paper is to take a step toward empirical resolution of which of these forces dominates, within the context of a particular retail market. Specifically, I use the literature on estimating differentiated product demand models to suggest a practical method for incorporating the actual distribution of consumers within a market (a non-parametric estimate of which is provided by the Decennial Census of Population) into a model of demand for retail products. To paraphrase Spence (1976), the welfare consequences of *any* government policy or business strategy can only be evaluated relative to the distribution of purchasers; we should clearly use our best estimates of the relevant one. In doing so, I build directly on the work of de Palma, Lindsey, von Hohenbalken, and West (1994), who take a first step along this road by calibrating a model of retail demand using the distribution of consumers provided by the census. Whether transport costs are more appropriately treated as a linear or quadratic function of distance is simply a question about the structure of consumer preferences over one particular product characteristic. In an empirical model, the structure of preferences can be inferred from observed behavior, given appropriate data.

I use the estimated demand model to examine the effect of changes in a theaters characteristics on its own- and its rivals- revenues. I find that many theaters' markets are effectively localized and, as a result, effectively quite small. A direct implication of localized markets is that the un-captured welfare gains from new products are derived only from local consumers and will therefore be modest.

[1]Regal Cinema's 1995 Annual Report (page 4).

In addition, business stealing effects are found to be small and to decline quickly with the distance between theaters.

I supplement the demand model with an estimated theater cost model using data from building permits to determine the relationship between theater size and its cost. Finally, I use the combination of demand and supply models to consider whether private theater scale choices are optimal. Since local monopolies do not suffer from a business stealing effect when firms in neighboring local market areas add capacity while even local consumer surplus effects are substantial, the results are consistent with the stance that the move toward large multiplex theaters is welfare enhancing. Perhaps somewhat unfortunately for static efficiency, the reason is that many of the theaters are effectively already local monopolies.

The plan for the paper is as follows. First, I briefly describe the structure of the exhibition market. Section 3 describes the demand modelling framework, while section 4 describes the new data set. Section 5 presents the econometric model and identification assumptions, while estimates and analysis of the demand side parameters is presented in Section 6. Section 7 presents estimates of the construction cost function for movie theaters and then combines the supply and demand models to consider their implications for the incentives for store scale decisions in retail markets. Finally, I conclude and outline directions for future research.

2 The Movie Exhibition Industry

In 1997 North American consumers went to the movies approximately 1.4 Billion times, generating Box office revenues of $6.4 Billion.[2] In contrast to the national distribution market, where the eight major players account for over 95% of sales, the largest five firms in the exhibition market operated just 41% of the approximately 32,000 screens. This is essentially unchanged since 1990 when C(5)=40%. However, for the entire post-war period relative fragmentation at the national level has masked high levels of market concentration.[3]

The most dramatic industry trend at the retail level is the increasing size of the multiplex (multi-screened complex). Until 1970, most theaters had only one screen. The first round of multiplex theaters partitioned the existing theaters into two, but by the mid 1970's exhibitors were purpose building new theaters with up to four screens. Today the largest theaters have *forty* screens, while those with twenty or more are common. In 2000, the MPAA report that 32% of theaters have a single screen, 43% of theaters are now known as "mini-plexes" with 2-7 screens, 20% have 8-16 screens and 5% have more than 16 screens. While many of the typically older and much smaller theaters still operate in small towns and niche locations, exiting theaters have typically been small while newly constructed theaters are larger. As a result, the average number of screens per theater rose from 3.6 to 4.9 between 1995 and 2000. The new "mega-plexes" are the latest phase of an extraordinarily dramatic three decade long evolution in the industry's market structure. This trend to larger stores is well documented across a range of retail markets and is also a source of considerable concern to policy makers. Perhaps the most controversial implication of this trend is the replacement of 'Mom and Pop' stores by big-box retailers such as Walmart.

[2] Motion Picture Association of America (MPAA) US Economic Review, available at http://www.mpaa.org/useconomicreview/2000Economic.

[3] For example, the data collected for this study shows one-firm concentration ratios are as high as 77% in medium sized markets such as Portland, Oregon even when markets are defined geographically very broadly.

The motivation for building large stores can emerge from either the supply side through economies of scale in construction, operation and/or distribution, or from the demand side through business stealing or market expansion effects. In this paper, I evaluate the demand side effects[4] and also economies of scale in construction. That leaves two other potentially important effects - economies of scale in operation and distribution.

An attractive feature of the exhibition market for studying retail scale decisions is that economies of scale in distribution are unlikely to be important: distribution is a simple task compared to most retail operations because of the small number of products being sold. Moreover, because the Paramount et al. consent decree signed in the late 1940's resulted in the vertical disintegration of the industry, distribution is also arm's length.[5] In fact, the most controversial element of the Paramount consent decrees that remains in force today requires that films be licensed on a theater-by-theater basis, on the merits.

In contrast, economies of scale in operation are important in the industry. The multiplex was a significant design innovation, allowing theater operators to take advantage of economies of theater scale arising initially from the shared facilities of foyer space and concession stands (provided film start times are appropriately staggered,) and the fact that a single cleaning team can service multiple auditoria. In addition, the ability to show the same film in multiple auditoria but only one film in each at a given time, clearly provides additional programming flexibility to the owner of a multiplex. These additional sources of economies of scale, while unfortunately omitted from the analysis, will act to reinforce my eventual conclusion that there is, if anything, an under-provision of auditoria.

Inevitably, there are features of the exhibition market that make it somewhat unique within retail. In particular, the structure of the revenue sharing licensing arrangements (which I shall describe later) are unusual, although parallels such as slotting allowances in other retail markets certainly do exist. Perhaps the most important source of unusualness is that the price for admission by final customers is essentially set in the market for an input, the film licensing market.

Before the Paramount decrees, distributors controlled admission prices primarily by owning the theaters. However, the consent decrees aimed to assure the rights of theater owners to set prices without interference from the distributors and today prices in the industry are chosen 'exclusively' by the largely vertically separate exhibitors. Since box-office revenue is contractually shared between the distributor and the exhibitor while revenues from candy and other concessions are not, exhibitors generally have an incentive to charge lower admission prices than distributors would like, thereby increasing the demand for high margin concessions sales. Licensing contracts rule out such behavior by specifying the admission prices for the three key demographic groups: adults, children (under 12's) and seniors (over 60's,) and a maximum percentage of admissions which can be discounted tickets (eg

[4]Reducing consumer search costs can provide a demand-side scale incentive. Those effects are particularly important for large specialty retailing stores who place many substitute but differentiated products in the same store. Since consumers decide which movie to attend before arriving at the theater, search costs do not play an important role in the exhibition market.

[5]In the landmark case of United States v. Paramount Pictures, et al., U.S. 334 US 1. (1948), the Supreme Court found the five majors (Paramount, Warner Brothers, 20th Century Fox, Loew's, and Radio Keith Orpheum) guilty of restraint of trade, including vertical and horizontal price fixing. The courts ordered both the vertical disintegration of the industry and, moreover, the divorced circuits (who would have owned or controlled all but a handful of the first run theaters in the largest twenty five US cities) were required to divest themselves of approximately one half of the 3,000 or so theaters they owned at the time. Some provisions of the consent decrees have recently been relaxed: some film distributors are now allowed to operate theaters again (Sony now own Columbia pictures and also Loews Cinemas.) However, most restraints remain in place on the original offenders.

2% in the first two weeks) that the theater commits to if the distributor chooses to show the film at that theater. Evidently a theater which promises to charge a low admission price in the market for film licenses is fairly likely to find itself unable to license popular films. In contrast, maximum retail price maintenance is per-se illegal in the U.S., making the retail sales price non-contractible in most other retail markets.[6]

3 The Demand Model

In this section I present an estimable model of retail demand that explicitly incorporates the observed locations of theaters as well as the actual geographic distribution of consumers within a market. By doing so, the demand model can help explain observed variation in market shares across the stores and, in addition, substitution patterns between stores depend directly on the distribution of consumers vis a vis the stores. These two key features of the model ensure that it will be useful in a large variety of retail settings.

The model I develop is within the broad class of mixed Multi-nomial Logit models, McFadden (1973). This class of models were first discussed in the context of aggregate data by Boyd and Mellman (1980) and Cardell and Dunbar (1980), and substantively further developed recently by Berry (1994) and Berry, Levinsohn, and Pakes (1995). For brevity I focus the discussion here on the model I use, however a full discussion of other feasible alternatives are provided in both Nevo (2000) and Davis (2000).

Suppose we observe $t = 1, \cdots, T$ days of sales data for each film $f = 1, \cdots, F^{ht}$ in each theater (house) $h = 1, \cdots, H^m$ in a set $m = 1, \cdots, M$ markets. A product is defined to be a film playing at a specific theater within a market at a given point of time. The conditional indirect utility consumer i obtains from watching film f at theater h is assumed to be of the form

$$u_{ifhmt} = x'_{fhmt}\beta - g(d(L_i, L_{hmt}); \lambda) + \xi_{fhmt} + \tau_f + \gamma_{c(h)} + \kappa_t + \epsilon_{ifhmt} \quad (1)$$

$$i = 1, ..., I, f = 1, ..., F^h, h = 1, ..., H, m = 1, .., M, t = 1, .., T$$

where (β, λ) are parameters, x_{fhmt} are K_1 observable product characteristics - including p_{hmt} the price of admission at theater h, τ_f denotes a film fixed effect, γ_c is a circuit (chain) fixed effect and κ_t is a time fixed effect. The distance from the consumer's location L_i to the theater's location L_h is denoted $d(L_i, L_h)$ and $g(\cdot, \cdot)$ is a function such as a linear or quadratic function of $d(L_i, L_h)$, known up to the $(K_2\text{x}1)$ vector of parameters λ. ξ_{fhmt} represents an unobserved (by the econometrician) product characteristic and ϵ_{ifhmt} is a mean zero individual and product specific stochastic term.[7]

[6] In addition to third degree price discrimination using patrons' age as the segmenting variable, time of day pricing is used on a limited basis: Admission to afternoon shows is typically offered for about 2/3rds of the evening adult admission price. Some theaters also offer reduced admission prices all evening on low demand days (eg., "Super Tuesdays.") However, the fraction of box office revenues obtained from admissions during each of these periods is believed to be small. In addition, admission price variation across regions of the auditorium, or across films within a theater, is extremely rare. On the whole, price discrimination then is used on a surprisingly limited basis within first run exhibition. This feature of the industry presumably reflects the costs of writing more complex contracts in the licensing market.

[7] An earlier version of this paper estimated a random coefficient version of this model. However, as has been common in the literature it proved extremely difficult to precisely estimate the random coefficients and so they are dropped in the specification reported here. See Nevo (2000) for example in the aggregate data mixed logit literature and also the discussion and references in Ruud (1996) in the individual level data mixed logit literature.

Examples of observed product characteristics include the number of screens, the type of sound system, whether the theater operates a consumer service line, is handicap accessible or operates a system for the hearing impaired. The unobserved product characteristic is assumed observed by, and common to, all individuals. Hence, at equal prices and differences, all consumers prefer a high ξ_{fhmt} product. Since attributes of theaters are advertised widely, I assume that both firms and consumers observe all the product characteristics and take them into account when making decisions.

A consumer characteristic at the center of this study is her location L_i. Each consumer is endowed with a location which determines her distance $d(L_i, L_h)$ from each theater. By allowing the distance term to enter non-linearly, the model can nest both the linear and quadratic transport cost specifications used by Hotelling (1929) and d'Aspremont, Gabszewicz, and Thisse (1979) and determining which is relevant is solely an empirical question. I use Euclidean distance so that a consumer's indifference curves in geographic space are concentric circles about her location. This formulation captures the idea that, all else equal consumers prefer to attend closer theaters, but that two theaters which are good substitutes are not necessarily physically close to one another; consumers living in the center of town may be indifferent between theaters located at opposite ends of town.[8]

Specification of the demand system is completed with the introduction of an "outside option:" some consumers decide not to attend any screening of a film. The conditional indirect utility from the outside option is

$$u_{i0mt} = \xi_{0mt} + \pi D_i + \epsilon_{i0mt}. \tag{2}$$

where D_i is a dx1 vector of the consumers demographic characteristics, π is a vector of parameters which measures how the taste for going to the movies varies with those demographic characteristics, namely age, income, and race. Without an outside good, a market wide change in any variable in the utility function (such as prices) will not change the quantities purchased. With an outside option, a uniform price increase will result in lower market sales. The mean utility of one option is not identified because adding a constant to the utility provided by each good does not change the individual's choice. Consequently, I normalize ξ_0 to zero.

I assume that consumers attend at most one performance of a film at a single theater on a single evening. A recent survey[9] reports that 94% of patrons choose which film at which theater to attend before arriving at the theater. Hence a model of consumer choice from the set of available alternatives provides a good description of consumer behavior.

By formulating the model as a static choice model, I have intentionally avoided some dynamic aspects to demand. For instance, in reality, individual consumers are unlikely to attend movies they have already seen, whereas the model assumes that every individual chooses from the full set of alternatives each day. Second, there is an important network externality that arise from word of mouth 'advertising.'[10] A third source of dynamics in demand could result from within theater capacity constraints.[11]

[8]While this may or may not be a good proxy for total travel costs, there is some evidence that straight line distance is a good proxy for travel time. For example, using data from New York State Department of Transportation, Phibbs and Luft (1995) find a correlation of 0.987 between straight line distance and travel times, although the number drops to 0.826 for distances below 15 miles. For trips below 15 miles, travel time per mile is generally greater than for longer distances.

[9]Daily Variety, October 22nd 1998, p.1

[10]The network effects are explored in detail in De Vany and Walls (1996) and certainly constitute an important explanation of the dynamic pattern of demand for a *single* film; particularly for art-house films whose distributors actively attempt to build word of mouth advertising.

[11]Since there is a substantial amount of within week seasonality in revenues, one might worry that the more popular days of the week suffer binding capacity constraints since admission prices vary little across days. While the structure of

I have abstracted from these dynamic effects, primarily because the very large amount of *cross-sectional* variation in the size and revenues of movie theaters seems highly unlikely to be explained by individual film dynamics which tend to aggregate out across films. Since explicitly modelling any of these aspects of the consumers' dynamic choice problem would render the model entirely computationally intractable while not dramatically improving the cross sectional explanatory power of the model, it seems reasonable to capture the dynamic features of the data that do exist in a simple reduced form way: using data on the number of weeks each film has played at each theater as well as time fixed effects in the conditional indirect utility function.

Given the choice model described above, the set of consumers who choose each product is defined as

$$A_{fhmt}(x_{\cdot mt}, \xi_{\cdot mt}; \theta) = \{(L_i, D_i, \epsilon_{ifhmt}) | u_{ifhmt} > u_{iglmt} \ \forall g, h, f, l \text{ s.t. } (h, f) \neq (g, l)\}$$

where $x_{\cdot mt}$ and $\xi_{\cdot mt}$, are the J^{mt}x1 observed and unobserved characteristics, $(L_i, D_i, \epsilon_{ifh})$ are consumer characteristics and $\theta = (\beta, \lambda, \pi)$ is a vector containing all the parameters of the model.

The aggregate market share of film f at theater h each evening is the sum of all consumers who choose that option:

$$s_{fh}(x, \delta; \theta_2) = \int_{A_{fh}} dP^*(L, D, \epsilon) = \int_{A_{fh}} dP^*(\epsilon) dP^*(D, L) \tag{3}$$

where $P^*(\cdot)$ denotes a population distribution function and the second equality follows from an assumption of independence of (D, L) and ϵ. The non-parametric estimate of the joint density of consumer demographics and locations $P^*(D, L)$ within each market is obtained from the sample provided by the decennial Census of Population. By directly incorporating the distribution of the population within each market into the model, variation in population density will help explain observed variation in demand across theaters within each market. Furthermore, the model has the desirable property that the substitutability of theaters depends on the location of consumers vis à vis stores.

4 Data

The data required to estimate the demand model consists of the distribution of consumer demographics and locations within each market $P^*(D, L)$, market shares for each film at each theater as well as theater characteristics such as admission price and theater locations, L_h.

The distribution of consumer demographics and locations were obtained from the US Census of Population. The Census Bureau partitions each county in the U.S. into sub-regions called census tracts, they construct a random sample of census returns and report a non-parametric estimate of the joint distribution of demographic characteristics (specifically for age, income and race) within each tract

the work week introduces popular days and times of day to shop quite generally, the seasonality is often most extreme at lower frequencies in other retail markets: for example from holiday periods, most notably Christmas. Whatever the frequency, if capacity constraints are empirically important they would likely result in observed sales that are somewhat flattened out, either across films within theater or across time for a given film as consumers substitute out of their most favored but constrained option. Neither patten is in anyway evident from the sales data: actual ticket sales demonstrate extremely skewed distributions both across films and across time (see table 3.) Since films are typically booked by theater circuit regional offices, while auditoria are assigned by the individual theater manager, the latter have a great deal of day-to-day flexibility to move films into auditoria that are appropriate for the anticipated audience numbers, substantively mitigating the effect of capacity constraints.

	min	max	mean	median	stdev
Counties per market	1	13	5.4	5.5	2.9
Tracts per market	24	819	264	220	184
Households per market	110,943	3,731,131	1,075,049	838,235	773,930
Households per tract	2	34,248	4,239	3,801	2,410
Sample size per tract	1	4,047	604	553	344
Sampling fraction per tract	0.03	0.7	0.15	0.14	0.05

Table 1: Note that though some of the sample sizes are low, and some of the sample fractions are low, these are not the same tracts. The correlation between sample size and tract size is 0.82 indicating that tracts with very small sample sizes also have very small numbers of people. For example, the decidedly lonely tract with only 2 people, has a sampling fraction of 50%.

$P^*(D|L)$ as well as the distribution of consumers across tracts, $P^*(L)$.[12] Table 1 describes the census tract data in detail. I use data from 36 market areas, partitioned into a total of $9,506$ census tracts covering a total number of approximately 39 million people.

Theater characteristics were obtained by first constructing a theater atlas consisting of cinema addresses for each market in the sample using newspapers, telephone directories, and the Internet. Next, during the summer of 1996, I surveyed each theater in the sample (873) by telephone to elicit theater level characteristics. A match between the EDI sales data and the theater survey data was found for 607 of the 873 theaters. Summary statistics for those theaters' characteristics are reported in Table 4 below.[13] In addition, I geocoded (attached longitudes and latitudes) the addresses using the *PhoneDisc Powerfinder Pro* phone book on CD-ROM.

The revenue data come from daily box office receipts, collected electronically each evening and made available in real time by *Entertainment Data Inc.* (EDI) . EDI covers all films distributed by Buena Vista, Columbia, MGM/UA, Orion, Paramount, Miramax, New Line, TriStar, 20^{th} Century Fox, Universal, and Warner Brothers.[14] Independent distributors (of which the sample includes 18) request revenue reporting on a film-by-film basis. All distributors also collect revenue data via slower proprietary channels and use the EDI service for flash reporting which, in turn, is used to guide advertising and promotion expenditures. EDI aggregates sales data across screenings (so revenue from matinee and evening performances are aggregated) and also across consumer types. Thus, I observe one sales figure for each film at each theater per day. Daily sales data for one week (June 21^{st} - June 27^{th}, 1996) were obtained from 36 markets.[15] Unfortunately, research budget constraints prevented the use of a longer

[12]The census does not report the actual joint distribution because of confidentiality concerns. I choose to use census tract data rather than census block data because the sampling error in the smaller census blocks would likely become an important source of error we would need to take into account when calculating standard errors for the parameters of the model.

[13]The data on THX auditoria, and those with DTS and Dolby digital sound systems were subsequently verified using information from the companies Internet sites, http://www.thx.com, http://www.dtstech.com and http://www.dolby.com respectively.

[14]In 1996, these eleven distributors accounted for 96% of box office revenue; National Association of Theater Owners (N.A.T.O. (1998)).

[15]The markets were chosen pragmatically. Initially I collected data for the 60 US cities for which local newspapers could be obtained in New York from specialist news-agents. The largest markets were removed when collecting data on theater characteristics proved impractical. A second reduction occurred for various data limitations, primarily when EDI

Variable	*Mean*	*Std·Dev.*	Min	Max	Obs.
Screens	6·370	3·399	1	24	607
Adult Price	5·602	1·331	.99	7.5	607
Consumer Service Line	·838	·368	0	1	607
Dolby Digital Sound (DD)	·349	1·005	0	10	607
Digital Theater Sound (DTS)	·806	1·412	0	12	607
Sony Dynamic Digital Sound (SDDS)	·319	1·767	0	24	607
THX	·307	1·177	0	12	607
Fraction of market population within five miles	·120	·098	.000	0.577	607
Fraction of market population within 5-10 miles	·207	·220	.000	0.488	607
Week	3·367	2·298	16	1	3121
First Week of National Release	0·102	0·303	1	0	3121

Table 2: The table shows the variation in theater and film characteristics across the 607 EDI theaters (3121 film at theater observations) in the sample. 'Screens' and 'Adult Price' describe the number of screens and adult admission price at each theater respectively. The remaining theater characteristics variables report counts of the number of screens with each type of sound system at the theater. THX is an auditorium quality certification provided by Lucas. 'Week' reports the number of weeks the film has played at that particular theater, while 'First week of National Release' indicates that the film is playing for the first week anywhere. The distribution of observed prices in the industry is bimodal, with lower price second-run theaters and higher priced first run theaters. Forty five of the 607 EDI theaters have adult evening admission prices below $3.

time series.

Table 3 presents summary statistics from the sales data. Revenue per film playing at an individual theater is highest on Saturday's with Friday and Sunday the next most popular days. Weeknights have substantially less attendance than weekend evenings. A striking feature of the revenue data is the dramatic range and skewness of observed sales. The least popular films playing at the least popular theaters have daily sales of literally only a few dollars while the median has sales of $500 on a weekend night. The mean is substantially higher than the median, with some films generating almost $30,000 in revenues per weekend night per theater.

The revenue data is used to define market shares by converting box office grosses into attendance (dividing by adult evening admission price) and expressing attendance as a fraction of the market population. Doing so suggests that approximately 1 in 150 people attend the movies each evening. Of course, some sales are in fact children, senior and matinee admissions but data limitations necessitate use of this approximation.[16] The measured market shares will accurately reflect the true market shares

did not receive data from an important regional theater circuit. EDI report theater coverage is approximately 97% of first run theaters. The sample coverage in this sample of markets is 81% of total screens, rising to 88% of price weighted screens. Coverage based upon fraction of revenues would certainly be considerably higher. These figures are lower than EDI's reported coverage rate (97%) because the figures here (i) include both first and second run screens, (ii) omit the largest markets (New York and Los Angeles) where EDI concentrates their coverage efforts and (iii) understate fraction of revenue covered since the distribution of sales is highly skewed.

[16]Since discount tickets are a relatively small proportion of admissions and cross sectional variation in discounting is likely limited, this approximation is probably not overly troublesome. For instance, since seniors (60+) are charged between 1/2 and 2/3rds of the adult admission price and account for only 8% of all admissions they correspond to only 4-6% of theater revenues. The fraction of admissions accounted for by under 12's is not reported by either N.A.T.O. or MPAA and I believe this indicates that it accounts for a relatively small proportion of sales

Day	mean	st. dev	median	min	max
Fri	1152.27	1709.38	531	4.00	25894
Sat	1442.28	1992.25	729	2.00	29812
Sun	1068.25	1554.88	520	3.00	23888
Mon	502.95	764.94	230	3.00	13385
Tues	462.66	666.38	226	3.00	10532
Wed	441.76	600.29	233	4.00	10889
Thur	420.15	587.00	228	2.00	12033

Table 3: Revenue for a single film at a theater by day. Units are 1996 US dollars. Number of observations = 20,008.

of those theaters with few discounted admissions, but under-estimate those at theaters where discount admissions are important. Since measured market shares are equalized to predicted market shares, at the true parameter values the implied unobserved product characteristics ξ_{fhmt} of theaters with low measured market shares will be correspondingly lower than their true values. If the proportion of discount admissions is correlated with the variables used as instruments, the estimated parameters will be biased. For instance, if theaters with a large number of senior admissions also have a large number of rivals with digital theater sound (the instrument for price,) then the estimated price coefficient will be biased upward toward zero.

5 Econometric Details and Identification

I estimate the parameters of the model using the techniques developed in Berry (1994) and Berry, Levinsohn, and Pakes (1995). The idea is to identify the parameters by requiring that the unobserved product characteristic ξ_{fhmt} is uncorrelated with a set of instruments at the true parameter value, θ^*. A nonlinear GMM estimator can then be constructed, exploiting the sample analogue to the identifying moment condition. A brief description is provided below and the reader is referred to Berry, Levinsohn, and Pakes (1995), Nevo (2000) and Davis (2000) for further details.

□ **Moment Conditions and Instruments.** Let f, h, m, t index films, theaters (houses), time and markets respectively. The full model is estimated by applying GMM to three sets of population moment conditions:

$$E\left[\overline{\xi}_{fhm}(\theta^*) \mid Z_{fhm}\right] = 0,\ E\left[\xi_{fhmt}(\theta^*)\right] = 0 \ \text{ for } t = 2, ..., T, \ \text{ and } E\left[e_{fhm}^{demographics}(\theta^*)\right] = 0$$

where ξ_{fhmt} is the unobserved (to the econometrician) quality of film f in theater h in market m on

- certainly less than the teenage $(12-17)$ demographic group who universally pay adult admission prices. (See http://www.mpaa.org/useconomicreview/2000AttendanceStudy/sld001.htm for further demographic details.) Anecdotally, attendance at bargain matinees is low relative to that at evening performances, but unfortunately no data is available to confirm that observation. Distributors heavily constrain use of discount coupons, especially during the high revenue weeks of a new film. A typical contract requires discount coupons to be used on less than 2% of total admissions and a proportionately smaller fraction of revenues. Overall then, the bias created by discounts and coupons is probably smaller than in most consumer products demand studies.

day t.

The first set of moment conditions restrict the average across time of the unobserved product characteristic, $\overline{\xi}_{fhm}$, to be uncorrelated with a set of instruments denoted by Z_{fhm}. The average across time is used to provide a conservative estimate of the amount of information in the sample, since ξ_{fhmt} typically exhibits significant positive autocorrelation. Berry, Levinsohn, and Pakes (1995) propose using a subset of own- and rivals-product characteristics to provide valid instruments. As those authors acknowledge, strong but largely unavoidable assumptions are required to justify instruments in differentiated product models. For instance, if firms choose own-product characteristics while knowing more than we do about ξ_{fhmt}, it will induce correlation between the observed and unobserved product qualities and bias our parameter estimates.

Using own-product characteristics as an instrument for themselves will be most problematic when they are easily adjustable control variables: most notably, unobservably high quality theaters may also tend to charge high prices. Sound systems, consumer service lines and other non-price theater characteristics are somewhat costly to adjust so I follow the literature and use non-price observed product characteristics as valid instruments for themselves. I instrument price with the number of rival screens which are equipped with Digital Theater Sound; lots of high quality rival screens should force a theater's admission price down, ceteris paribus.[17]

Perhaps the most problematic source of endogeneity among product characteristics is introduced when unobservably high quality theaters attract high 'quality' films from distributors. Since film allocations are made on a relatively high frequency basis, film characteristics may not provide valid instruments for themselves. An alternative is to estimate the non-linear parameters using moment conditions based on a transformation of the unobserved product characteristic to remove film characteristics. For example, applying a 'within' film transformation, the equation $\delta_{fht} = x_{fhmt}\beta_1 + x_f^2\beta_2 + \xi_{fhmt}$ becomes $(\delta_{fhmt} - \overline{\delta}_f) = (x_{fhmt} - \overline{x}_f)\beta_1 + (\xi_{fhmt} - \overline{\xi}_f)$ so that the pure film characteristics are differenced out of the regression equation before estimation. Since estimation on the within equation would be identical to including a full set of film dummy variables in the untransformed equation, that is the approach taken here. Nevo (2001) makes a similar argument.

The second set of moments identify the $(T-1)$ day fixed effects κ_t in mean utility which are used to capture the within week seasonality observed in the data.

The final set of moment conditions use data on attendance probabilities for various demographic sub-groups obtained from a 1996 survey of American consumers by the market research firm, Mediamark. The data come from a survey of approximately 20,000 individuals performed in 1996 and provides the probability of attendance by age, income, and race categories in their sample in addition to the survey sampling probabilities for each demographic group. Define $A = \{i|\text{i attends}\}$ and $D_g = \{i|\text{i in demographic group g}\}$ for $g = 1,..,G$ to be the set of people who attend and in each demographic group respectively. In the expression above, $e_{fhm}^{demographic} \equiv (e_{fhm}^{age'}, e_{fhm}^{income'}, e_{fhm}^{race'})'$ a Gx1

[17] I follow a somewhat different approach to previous authors in the literature; deliberately estimating an exactly identified model rather than imposing a large number of moment conditions. The aim is to avoid the problems emphasized in the recent econometric literature on 'weak-instruments' (see Bekker (1994) and Stock and Staiger (1997)) which has shown that substantial finite sample biases are highly likely whenever models are greatly over-identified by instruments that each have little identifying power. The advantage of using a just identified approach is that I can be absolutely clear about which, albeit often strong, assumptions are identifying which parameters of the model. Empirically I found the approach provided considerably more robust results than estimating heavily over-identified models. In Table 4, I report the price-instrument regression to establish the correlation between the number of rival digital theater sound screens and prices. Other potential instruments for price such as the distance to the closest theater were considered but were not robustly correlated with admission price.

vector of moment conditions, one for each demographic sub-group D_g and

$$e^g_{fhm} \equiv \left(\int_{D_g} \overline{s}_{fhm}(\theta; L, D) dP^*(L, D) \right) - \mathbb{P}\{A|D_g\}^{observed}.$$

where $\overline{s}_{fhm}$ denotes the predicted market share, averaged across time. These "macro-"moment conditions are used to identify the way tastes for going to the movies vary across demographic groups. Imbens and Lancaster (1994) suggest using this kind of moment condition and Petrin (1998) also uses similar ones successfully in his model of demand for automobiles.

The distance coefficients are identified by using the restriction that the unobserved theater characteristic is uncorrelated with the number of people who live within a five, and five to ten, mile radii of the theaters. These moment conditions were motivated by examining reduced form regression equations which show a strong positive relationship between the number of people who live close to a theater and its market share, a feature of the raw data which strongly suggests that transport costs are important. This identification strategy requires that we assume theater location is an exogenous product characteristic and clearly that is not an entirely innocuous assumption. Like all product characteristics, location, and thereby distance to consumers and distance from rivals, is presumably a choice variable. If so, the presence of large numbers of consumers will induce the presence of a large number of rival screens, lowering the theaters observed market share. In that case, the estimated relationship between market share and numbers of customers will be flatter than if location were truly fixed. As a result, if this supply side effect is a substantive effect, my identification strategy will likely underestimate transport costs.

6 Estimation Results and Analysis

□ **Reduced Form Results.** The reduced form results are reported in Table (4). Column (1) reports the "first stage" price instrument regression, demonstrating the ways prices vary with theater characteristics. The patterns that emerge are intuitive. For instance, theaters with consumer service lines, high quality sound systems or large numbers of people living close to them charge higher admission prices. In addition, the estimates show that the instrument used to identify the price coefficient in the demand model, the number of digital theater sound systems operated by rivals, is highly conditionally correlated with adult admission price, as required.

Columns (2) and (3) report parameter estimates for the product level MNL model with an unobserved product characteristic. This model is estimated using a simple two stage least squares regression procedure (see Berry (1994)) and provides a well understood benchmark against which to compare the results from the full model. It is also particularly useful as a specification aid for the full model, which is currently very CPU intensive to estimate.[18] In particular, the results aim to demonstrate that there are clear and intuitive relationships between the observed market share data and both theater product characteristics and, most importantly, the geographic distribution of consumers vis a vis the theaters. In column (2), each of the estimated mean utility parameters have intuitive signs. Consumer service lines, DTS, SDDS, DD and THX each provide positive marginal utility. The longer the film has played at that particular theater, the lower the utility it provides. Strikingly (if unsurprisingly) large is the

[18] A typical run with 5,000 simulated consumers currently takes at least 48 hours on my 800MHZ PC, even with good starting values and extensive code optimizations; the time intensive portions of the algorithm were coded directly in C.

	Price Regression		Multinomial Logit				Full Model	
Variable	Parameter	$\|t\|$	Parameter	$\|t\|$	Parameter	$\|t\|$	Parameter	$\|t\|$
constant	2.855	6.875	-8.859	25.76	-8.822	26.08	-10.80	10.76
consumer service	0.201	8.671	0.139	1.617	0.008	0.086	0.083	0.546
DTS	0.028	2.508	0.045	5.491	0.079	7.011	0.044	3.462
SDDS	0.047	3.117	0.015	2.123	0.031	2.602	0.040	5.082
screens	0.061	3.672	0.032	6.346	0.027	3.350	0.039	2.466
Dolby Digital	0.027	2.684	0.036	3.615	0.023	1.638	0.023	1.585
THX	0.049	4.461	0.026	2.635	0.034	2.483	0.011	1.063
Week	0.191	4.606	-0.027	2.115	-0.024	1.579	-0.039	1.919
First week of National Release	0.619	5.157	1.937	7.064	1.978	6.855	1.755	3.597
Adult Admission Price	-	-	-0.193	1.726	-0.182	1.547	-0.096	0.453
Counts of Households interacted with Theater Characteristics								
Five miles	0.040	2.016	1.131	4.823	0.222	0.336	-	-
Five to Ten miles	0.074	3.410	0.267	1.617	0.249	1.494	-	-
Five*Consumer Serv.	-	-	-	-	1.420	2.784	-	-
Five*DTS	-	-	-	-	-0.342	3.597	-	-
Five*SDDS	-	-	-	-	-0.171	1.680	-	-
Five*Screens	-	-	-	-	0.022	0.468	-	-
Five*Dolby Digital	-	-	-	-	0.199	2.147	-	-
Five*THX	-	-	-	-	-0.082	0.571	-	-
Five*Week	-	-	-	-	-0.034	0.683	-	-
Five*First Week	-	-	-	-	-0.569	1.309	-	-
Instrument for Price in Demand Model								
Rival DTS Screens	-0.307	6.417	-	-	-	-	-	-
Non-Linear Parameters for Full Model								
$\gamma_{distance}$	-	-	-	-	-	-	-0.114	3.040
$\gamma_{distance^2}$	-	-	-	-	-	-	0.002	2.787
$\pi_{age<25,outside}$	-	-	-	-	-	-	-2.496	10.31
$\pi_{25<age<35,outside}$	-	-	-	-	-	-	0.133	0.666
$\pi_{35<age<45,outside}$	-	-	-	-	-	-	0.550	2.468
$\pi_{45<age<55,outside}$	-	-	-	-	-	-	-0.272	1.235
$\pi_{55<age<65,outside}$	-	-	-	-	-	-	-0.112	0.505
$\pi_{inc<30,outside}$	-	-	-	-	-	-	1.887	8.476
$\pi_{30<inc<40,outside}$	-	-	-	-	-	-	-0.337	1.784
$\pi_{40<inc<50,outside}$	-	-	-	-	-	-	-1.107	6.010
$\pi_{50<inc<60,outside}$	-	-	-	-	-	-	-1.343	6.500
$\pi_{black,outside}$	-	-	-	-	-	-	-2.014	12.60
$\pi_{other,outside}$	-	-	-	-	-	-	-4.216	8.741

Table 4: Number of observations is 20,008. Each regression is estimated using moment conditions analogous to the equations in 5. Each model is exactly identified and includes unreported film, circuit and time fixed effects. All t statistics are calculated using robust standard errors and allow for arbitrary across time correlation structure. In the column headed 'Price Regression,' the dependent variable is Adult Admission Price and the explanatory variables are of three types: (i) non-price theater characteristics, (ii) interaction variables used as instruments to identify the distance related non-linear parameters in the full model and (iii) the instrumental variable for price in the demand model; the number of rival screens with digital theater sound systems. In the columns headed 'Multinomial Logit Model' (MNL) the dependent variable is $ln(s_{fhmt}) - ln(s_{0t})$. In column (3), the specification introduces interactions between the proportion of the markets households who live within five miles of the theater and theater characteristics. The final column reports full model estimates, calculated using 150 simulation draws per market area, a total of 5,400 simulated consumers. The value of the outside good is allowed to vary systematically with the age group of the consumer. The standard errors of the parameters used to compute the t statistics take into account the variance in the estimates due to simulation error by bootstrapping that component of the variance in the moment conditions. The standard errors reported here are calculated using 50 repetitions of the bootstrap.

coefficient on the indicator variable showing whether the film playing is on its first week of national release.

Geographic characteristics are included by constructing additional "theater" characteristics: the fraction of people in the market that are living within five miles and within five to ten miles of each theater. The former has a highly statistically significant positive impact on the market share attained by a theater while the latter is close to conventional statistical significance. Incorporating geographic 'theater characteristics' in this way enables this MNL model to explain observed variation in market shares across theaters; those with a large fraction of the market population nearby have ceteris paribus higher market shares. However, in contrast to the full model, the substitution patterns identified from the MNL model continue to impose the unreasonable Independence of Irrelevant Alternatives (I.I.A.) assumption. Thus, for example, the estimated marginal effect of an increase in population near to a theater will by construction depend only the observed market shares of the theater.

Column (3) attempts to isolate which theater characteristics attract consumers into the theater. For instance, it seems perfectly reasonable to expect that theaters with high quality sound systems draw more customers from further away than those without. Unfortunately, this effort is not entirely successful. The effects that are precisely estimated are due to the various kinds of sound systems, whether the theater has a consumer service line and whether the film is in the first week of a national run. Each of these variables can help explain the variation in market shares across theaters with the same population living close to them. However, the interaction effects and the direct effect of population suffer from multi-collinearity and it does not appear possible to separate their effects in this data-set. In particular, the different signs reported from the effect of similar sound systems (dolby digital and digital theater sound/SDDS) are not reassuring.[19] As a result, the estimates of the full model I report incorporate only the direct effects of distance.

The price coefficient is used to translate units of utility into dollars, but unfortunately it can only be moderately precisely estimated. Uncertainty about the price coefficient translates immediately into uncertainty about the absolute dollar figures of welfare effects and therefore I shall be cautious and perform robustness checks for the price parameter. That said, the results are similar to those reported in Davis (2002a) where I use data from a three week marketing experiment undertaken by Hoyts theaters to observe the reaction of sales to large variation in the adult admission price in first run theaters. During the period of the study, the adult evening admission price declined for a three week period from \$7.75 to \$5, before rising to \$8. In that study, the exogenous variation in prices allowed the price coefficient in a demand model to be precisely estimated.

□ **Full Model Results.** Column (4) reports parameter estimates for the full model. In each case, the linear parameters have intuitive signs and overall remain at values relatively similar to those from the MNL model. Both the full model and the MNL model augmented with geographic 'theater' characteristics allow variation in market shares to be explained by the distribution of consumers and their characteristics within a market. However, only the full model has substitution patterns that depend directly on the distribution of consumers vis a vis theaters.[20]

[19]Unreported full model estimates with interactions place a negative coefficient on the direct utility from digital theater sound (dts) and an insignificant interaction between distance and the dts. The signs of these effects are consistent with high quality sound systems attracting consumers from further away from the theater, which is intuitive. Unfortunately, despite extensive effort to persuade the data to reveal more about the nature of these important interaction effects, no robust and statistically significant results were obtained.

[20]Once geographic and demographic variables were allowed for, no further role for consumer taste heterogeneity could

	Distance band around theater (miles)				
	$0-5$	$5-10$	$10-15$	$15-20$	$\%Decline$
Quantile	Change in Theater Revenue				
0.05	12	6	4	3	67
0.25	88	55	36	24	73
0.5	220	148	112	71	68
0.75	524	381	277	169	68
0.95	1463	1058	745	478	68
Quantile	Change in Industry Revenue				
0.05	941	919	721	523	45
0.25	2228	2579	2206	1538	30
0.5	4093	3946	3630	3011	27
0.75	6734	6506	6154	5286	22
0.95	12984	9961	10675	9840	25

Table 5: The marginal effect of local population growth on theater revenues. Since the distribution of revenue changes across theaters is highly skewed, as a result of the importance of theater size and quality levels on the theater level effect, I report quantiles of the distribution.

The full model suggests that travel costs reduce sales significantly. The full model's parameter values suggest that the implied cost of travel is non-linear, with a marginal cost of travel given by $\frac{-0.114}{-0.096} + 2\frac{0.002}{-0.096}distance = 1.18 - 0.04distance$ cents. Reducing the distance a consumer is required to travel by one mile decreases the amount they would be willing to pay for admission by approximately \$ 1.18 initially, but the marginal cost of travel decreases as the distance travelled increases.[21] Unfortunately the magnitudes of the estimated travel costs are very sensitive to the imprecisely estimated price coefficient, although the shape of the estimated transport cost function is not.

In the full model, consumer tastes are allowed to vary in a systematic way with their demographic characteristics. Important interactions between age, income and race with the outside good reflect the mediamark survey data's evidence that younger and richer consumers have a greater preference for attending movie theaters than their poorer and older contemporaries. One demographic category is omitted from each partition of the population, for example age parameters reflect demand relative to a person over sixty. These demographic parameters show that older consumers have significantly better (for them) outside options than younger consumers (dramatic arts, opera, going to Paris for the weekend...) and/or a higher opportunity cost of time. However, richer consumers enjoy going to the movies ceteris paribus; it is a normal good. The 'other' and 'black' demographic categories follows the definition of the 1990 census. 'Other' includes both Hispanics and Native Americans. Both are estimated to have a significantly greater preference for attending movies than whites, though they obviously account for a much smaller fraction of the population and audience.

The parameter estimates themselves are stated in terms of utility and are therefore difficult to interpret. To aid interpretation of the results, in the next two tables I report a selection of marginal effects from the full model.

be identified. In consequence, the results reported here do not allow for random coefficients on other variables.

[21] Several people have suggested that the appropriate formulation of travel costs should be a fixed fee and then a linear cost. This would be an attractive specification, but it cannot be evaluated within the random coefficient logit framework since by assumption all consumers buy all goods with some probability.

	Theater Characteristic						
	CS	*DTS*	*DD*	*SDDS*	*Price*	*THX*	*Screens*
Quantile	Change in Theaters Own Revenue						
0.25	771	400	357	98	−3562	204	361
0.50	1787	928	828	227	−1899	473	837
0.75	3338	1734	1547	424	−829	884	1564
	Change in Rival Theaters Revenue						
0.25	−496	−258	−230	−63	93	−132	−233
0.50	−231	−120	−107	−29	243	−61	−108
0.75	−88	−46	−41	−11	528	−23	−41

Table 6: The table reports the marginal effect of a one unit exogenous increase in a theater's product characteristic on weekly revenues. All figures correspond to changes in revenue over the week of the sample in 1996 and report the results of 607 marginal changes in characteristics across the 607 theaters in the sample.

The first panel in Table 5 reports the predicted theater revenue change from an exogenous 10,000 person increase in the size of the population living around a theater. The population growth experiment is performed for every theater in the sample and quantiles from the distribution of outcomes across theaters are reported. The middle four columns show how the changes in revenue vary when the additional population is distributed at increasing distances from the theater; the population growth is distributed across the census tracts in one of the four bands around the theater in proportion to the existing population. The four bands are $[0, 5)$, $[5, 10)$ $[10, 15)$ and $[15, 20)$ miles from a theater respectively. All reported figures are weekly. Thus, 25% of theaters recorded a predicted increase in weekly revenues of \$88.07 or less when the population living within five miles of the theater is increased by 10,000 people. The second panel reports the marginal effect of the identical population growth on industry weekly revenues while the final column shows reports the percent decline in theater (industry) revenue growth from the second column (< 5) to the fifth, $[15, 20)$.

Looking across the first panel, it is evident that theaters benefit most from local population growth. Growth in the number of consumers living between fifteen and twenty miles from a theater are predicted to increase a theaters revenues only by 1/3 of the amount that an equivalent growth in local population would have. The second column shows that the corresponding drop in the growth of aggregate industry revenues is much less dramatic as consumers are located further away from an individual theater; many simply attend another theater. However, since population density in a market is typically far from uniform and theaters tend to be located around towns, when consumer growth occurs sufficiently far from densely populated areas the effect on aggregate industry revenue is indeed muted.

In Table (6) I report the marginal effect of a change in a theater's characteristic on its own, and the aggregate of its rivals, revenues. For example, the DTS column reports the predicted impact of one additional Digital Theater Sound auditorium on own and rival revenues. The only exception is the admission price column: since a change in a theater's own price from p_h^1 to p_h^0 can be decomposed into two effects: $Revenue_h^1 - Revenue_h^0 = p_h^0(s_h^1 - s_h^0) + (p_h^1 - p_h^0)s_h^1$, I report the first component in the table for comparability. The second component, the increase in revenue coming from the higher admission price, has an upper quartile of 6110, a median of 3525 and a lower quartile of 1669.

The most striking feature in the table is that the own theater effects are uniformly larger than the cross theater effects. That suggests the theaters are relatively close to operating in their own, substantively if not completely separate market areas. It is interesting to note that installing a new

Sony Dynamic Digital Sound (SDDS) system is predicted to have substantially less of an impact on theater revenues than either Dolby Digital or Digital Theater Sound system. This picks up the pattern in the data that the former were primarily adopted by Sony theaters, who installed those systems in all their theaters in an attempt to make that sound system the standard for all theaters.[22]

The distribution of the total effect of a $1 price increase is positive, with quartiles 2548, 1626 and 840. Thus, ceteris paribus, increasing adult admission price is predicted to increase box office revenues at the existing price. If the marginal cost of reducing patrons were zero, this would certainly suggest prices are lower than optimal. However, the cost of increasing admission price is reduced concessions sales. Theaters typically retain an average of approximately 40% of the box office revenues while concession sales are approximately 30% of box office revenues. Hence for the prices to be optimal for the theater, lost concession sales would be approximately $0.3p_h^0(s_h^1 - s_h^0)$ while the increase in theater revenue would be $0.4(p_h^0(s_h^1 - s_h^0) + (p_h^1 - p_h^0)s_h^0)$. Thus, for example the top quartile would see increased box office gains of $0.4(6110 - 3562) = 1019$ while concession sales would decline by $0.3(3562) = 1068$. Somewhat remarkably given all the assumptions involved, these results do appear to be at least broadly consistent with prices being chosen approximately optimally by the theater.

□ **Distance and Cross Revenue Effects.** How much does geographic differentiation insulate retailers from competition? Consumer borne travel costs imply that, ceteris paribus, stores close to one another provide good substitutes, those further apart worse.

The U.S. anti-trust authorities appear to believe that stores do provide substitutes for one another, but that there remains substantial opportunities to exploit market power particularly when a single chain operates multiple outlets in one area. This is evident from their behavior: In an effort to avoid the exploitation of local market power from geographic product differentiation they frequently require that individual retail stores are sold off to create 'effective' competition. The recent merger between Sony and Cineplex Odeon provides an example where divestment of specific theaters were required: 14 theaters on Manhattan and 11 theaters in Chicago.[23] Such a strategy will evidently only be effective if retailers are not already effectively local monopolists.

In an effort to describe the extent of competition between stores, Table 7 reports a descriptive regression which relates the estimated change in weekly revenue at theater k resulting from a unit marginal change in the characteristic of theater j, to the distance between the theaters, the number of films playing at both theaters, and whether the theaters are owned by the same theater chain. The table is an attempt to show the business stealing effects resulting from theaters decisions about their own theater characteristics.

The sign patterns of the results are extremely intuitive. At zero distance between the theaters, an increase in a theater characteristic that provides positive (negative) utility is predicted to reduce (increase) rival theater's revenues. Theaters which show a large number of the same films demonstrate much larger cross-revenue effects, as do theaters owned by the same circuit. The presence of both of

[22] Each sound system records/sychronizes sound to/with the film using a different technology, currently making it necessary to place multiple versions of the sound track onto each film.

[23] Another recent example from Connecticut was the July 1996 consent order following the acquisition of Edwards food stores by Ahold, parent company to the rival supermarket chain Stop and Shop. Ahold was required to divest 26, specifically identified, Edwards stores from a total acquisition of 69. Indeed, the specifics of location make regular appearances at Department of Justice merger reviews and consulting firms sell their Geographic Information System (GIS) capabilities to provide "powerful visual testimony" (Charles River Associates 'Insights', 1997) in cases involving geographic differentiation. A significant use of the tools developed here will hopefully be to move such analysis from visual testimony toward a fully fledged empirical analysis.

	full model															
Characteristic	CS		DTS		DD		SDDS		Week		Price		THX		Screens	
Variable	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$	Param.	$\|t\|$
const	-27.36	(16.0)	-14.23	(16.0)	-12.69	(16.0)	-3.48	(16.0)	12.32	(16.0)	29.11	(15.9)	-7.25	(16.0)	-12.83	(16.0)
distance	0.12	(3.1)	0.06	(3.1)	0.05	(3.1)	0.01	(3.1)	-0.05	(3.1)	-0.13	(3.1)	0.03	(3.1)	0.05	(3.1)
$Distance^2$(1x10^{-4})	-2.67	(0.5)	-1.37	(0.4)	-1.23	(0.4)	-0.33	(0.4)	1.17	(0.4)	2.73	(0.4)	-0.70	(0.4)	-1.24	(0.4)
$Distance * samefilm$	0.19	(10.6)	0.10	(10.6)	0.09	(10.6)	0.02	(10.6)	-0.08	(10.6)	-0.21	(10.6)	0.05	(10.6)	0.09	(10.6)
$Distance^2 * samefilm$(1x10^{-3})	-2.22	(7.3)	-1.15	(7.3)	-1.03	(7.3)	-0.28	(7.3)	1.00	(7.3)	2.37	(7.3)	-0.59	(7.3)	-1.04	(7.3)
Same film	-7.76	(32.0)	-4.04	(32.0)	-3.60	(32.0)	-0.99	(32.0)	3.50	(31.9)	8.28	(31.9)	-2.06	(32.0)	-3.64	(32.0)
Same chain	-2.50	(5.1)	-1.30	(5.1)	-1.16	(5.1)	-0.31	(5.1)	1.12	(5.1)	2.66	(5.0)	-0.66	(5.1)	-1.17	(5.1)

Table 7: The dependent variable $\Delta Revenue_k(\Delta x_j)$ is the estimated change in weekly revenue at theater k resulting from a unit marginal change in the characteristic of theater j. This prediction is calculated for each pair of theaters in the sample using the full model. The regressions summarize the results. Same film counts the number of films playing at both theaters while Same chain is a dummy variable denoting that the two theaters are owned by the same theater chain. Market fixed effects are included in both specifications.

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these effects should presumably be of some reassurance to anti-trust authorities. The former suggests that the active encouragement of competition between theaters for films increases cross revenue effects while the latter suggests that encouraging a diversity of ownership of nearby theaters will likely increase competition. As distance between the theaters increases, the magnitude of the cross revenue effects decline toward zero. The interactions between Same Film and Distance show that decline in distance occurs at a slower rate when two theaters show a large number of similar films.

While the sign patterns are extremely intuitive and encouraging for the antitrust authorities, the magnitudes of the cross- revenue effects are actually rather small. In this industry, that would appear to be consistent with both management beliefs (cf., the opening quotation) and also perhaps with what we know about the magnitudes of travel costs; an individual should not rationally travel very far to save 5% of the admission price (ie., 40 cents of a $7.50 admission.)[24]

At least one substantive caveat should be given to the conclusion that the business stealing effects are small since the data were unable to empirically determine the magnitude of interaction effects between theater characteristics such as digital sound and travel cost. If improving theater quality substantively increases the distance consumers are willing to travel to attend high quality theaters then these results will likely understate the importance of the business stealing effects of those theaters and the extent of geographic competition as a result. This is clearly an important issue, but it is one which the data limitations mean I must leave for future research.

7 Entry and Scale

In this section, I consider whether movie theaters are likely to engage in socially excessive or insufficient entry - in the sense of building theaters which are too large or too small. Doing so requires the model of demand developed above and also a model of the cost of supplying theaters of varying scales. I estimate the latter using data on theater costs.

Mankiw and Whinston (1986) showed that business stealing generally results in socially excessive entry in homogeneous product industries. In contrast, when products are differentiated, the incentive to introduce excessive numbers of products may be tempered, or indeed overwhelmed, by the inability of firms to captured as profits the consumer welfare gains resulting from increased product diversity. Remarkably, in a differentiated product industry with demand described by the multinomial logit demand system, Anderson, de Palma, and Nesterov (1995) show that free entry never results in more than one fewer product than a social planner maximizing welfare would provide. However, this result does not generalize to richer demand systems and emerges because individuals are identical except for the additively separable random Type I extreme value random term in the logit model.

In the empirical model developed here, three effects act in concert to suggest that there is under provision of products in the market. First consumers are heterogeneous, beyond the logit error heterogeneity, ensuring the returns to diversity can be substantial. Second, the revenue sharing arrangements in the movie industry - which ensure that theater owners only receive a fraction (approximately 40%) of box office revenues - greatly temper the effective magnitude of the business stealing effect. Third, there are fixed costs of entry. If there are fixed costs and also large amounts of un-captured consumer surplus are provided by the first few screens/products, then products can be unprofitable to provide even when they are welfare enhancing. (This latter mechanism is described further below.)

[24]The cost of transport in a privately owned vehicle is approximately 31 cents per mile according to studies by the US General Services Administration (GSA). [May 23, 1996 Federal Register page 25802, Vol 61, No 101.]

	Theater Circuit				
	Regal	Carmike	GCC	AMC	Parameter
Revenues					
Admissions	69	69.5	68.6	66	α^a
Concessions	31	30.5	31.4	34	$1-\alpha^a$
Costs					
Film Rental	37.7	37.2	34.7	33	α^d
Concessions	3.5	4.1	6.1	5	α^c
Theater Operations	31.8	39.4	49.2	38	α^o
Multiple	0.39	0.28	0.15	0.36	$\phi \equiv \frac{1-\alpha^d-\alpha^c-\alpha^o}{\alpha^a}$

Table 8: Circuit wide revenues and costs as a percentage of total theater revenues. Sources: Various annual reports 1995/1996.

I consider three possible objective functions that determine the optimal scale of the theater. First, that a privately owned theater maximizes individual profits, second that a market wide cartel operates to maximize industry profits and finally that a social planner maximizes welfare defined as the sum of consumer surplus and industry profits.

In each case the objective function is described by

$$Lifetime\ NetRevenue + \chi Lifetime\ Consumer\ Surplus - Costs$$

where $\chi = 1$ in the social planner's objective and zero in the other two cases. In the first case, each term is calculated using only the data for the individual theater. In the social and collusive cases, the relevant components are for the whole industry including the new theater. In each case, Consumer Surplus is calculated relative to the situation of building no new screens at a specific location and given the existing distribution of product characteristics including theater locations. I now turn to estimating each of these components and then use the model to analyze the incentives for new product provision.

□ **Estimating Lifetime Net Theater Revenues.** The demand model developed above can directly provide an estimate of daily theater box-office revenues at a new theater on each day in the sample period. However, we need to translate that estimate into a measure of lifetime revenue for the theater, net of film rental, concession and theater operations costs. Substantial theater revenues do come from concession sales and the (high) margins on concessions are retained by the theater operator. In contrast, film rental costs are contractually a fraction of box office revenues.
Table 8 shows that these factors are mainly stable as a proportion of revenues across theater chains

and consequently can be adjusted for at least approximately using the relation[25]

$$Lifetime\ Net\ Revenue \equiv \psi \frac{(1-\alpha^d-\alpha^o-\alpha^c)}{\alpha^a} Weekly\ Revenue,$$

where ψ is a parameter which operates to inflate weekly net revenue to provide an estimate of lifetime theater revenues. Clearly this calculation clearly has the flavor of a back of the envelop calculation. Nonetheless, the qualitative results described below prove entirely robust to variation in these new parameters within substantial ranges and are designed to demonstrate and evaluate the economic forces at work. Similarly, define

$$Lifetime\ Consumer\ surplus \equiv \psi Weekly\ Consumer\ Surplus.$$

In addition, I must make assumptions about the allocation of the quality of products assigned to the screens at a new theater. If a large number of blockbuster films are available then one would expect the numbers of screens that can be profitably operated to be much larger than if a theater can only attract second run films. I flexibly parameterize the utility provided by new screens by assuming that product quality is a vertical characteristic which evolves with the scale of the theater as a quadratic function. Specifically, assume that the utility provided by the f^{th} new screen at a new theater is described by

$$u_{fh} = \beta_0 + \beta_p p_h + \beta_1 f + \beta_2 f^2 + \lambda_1 d(L_i, L_h) + \lambda_2 d(L_i, L_h)^2 + \epsilon_{fh}, \text{ for } f = 1, .., F^h$$

thus if $\beta_2 < 0$ then eventually the quality of additional products will decline as f increases. Since the estimated coefficient on the number of screens at the theater was positive I allow (β_1, β_2) to sometimes take on values which involve an initially increasing utility in theater size. Denoting the maximum of this quadratic function as f^{max} I consider $\beta_2 \in \{-0.01, -0.025, -0.05, -0.1\}$ and $f^{max} \in \{1, 3, 5, 10, 15\}$ which can be ensured by setting $\beta_1 = -2f^{max}\beta_2$. In addition, I set β_0 equal to the estimated constant term and β_p to the estimated price coefficient.[26]

□ **Estimating Theater Construction Costs.** Estimates of construction costs are, at least in principle, publicly available for individual buildings from county or municipal building permit authorities. For each theater in the sample, I contacted the theater's permit authority to obtain the relevant figures.[27] While many permits were missing, I did manage to obtain cost data for 140 theaters in the sample.

[25] The table shows that there is considerable variation in the reported cost structure of the firms evident in the Theater Operations category. Theater operations costs include wages, cleaning costs and also theater leasing costs. The variation reported across the chains appears to result primarily from the different accounting treatment of leased and owned theaters. The lower operations numbers tend to reflect a higher proportion of owned theaters. Consequently, the higher theater operations proportions are likely more representative of overall economic cost structure. Since I tend to find that the socially optimal theater scale is greater than the private scale, in the scale experiments I report results that provide the maximal incentives for private provision; using the Regal numbers. As a result, the qualitative features of the results will be robust to all variation in these parameters that results in an overall multiplying factor which is lower than Regal's 0.39.

[26] As an additional robustness test in light of the difficulty of precisely estimating the price coefficient, I also considered other values of the price coefficient $\beta_p \in \{-0.05, -0.1, -0.25, -0.5\}$. The qualitative results do not change from those reported below, although the magnitudes of the business stealing effects do.

[27] Unfortunately, the success rate was low, (about 15%), since many authorities only computerized records during the last ten years and finding the permits required a staff member to search manually through old files. Records were often missing or incomplete. Where possible, I verified and/or augmented the permit information using building valuations

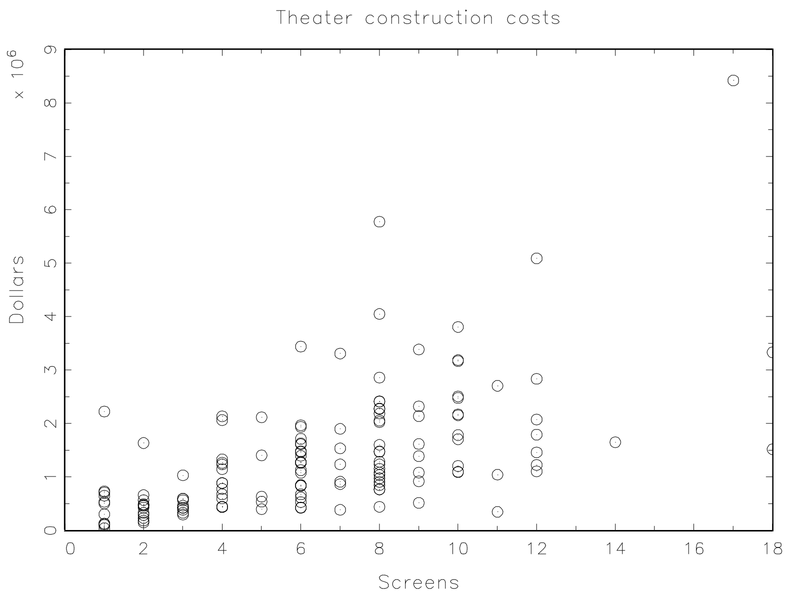

Figure 1: Theater construction cost data in 1996 dollars as a function of theater scale.

Figure 1 presents the construction cost data as a function of theater scale. The most expensive theater in the sample cost \$8.25 million to build, while the cheapest theater cost only \$42,000.[28] As expected, average construction costs increase as the theater scale increases, moreover the spread of the distribution also increases dramatically with scale.

Table 9 reports an hedonic regression using the construction cost data. The estimated model of theater costs is

$$C_i = \alpha_0 + \alpha_1 s_i^L + \alpha_2 (s_i^L)^2 + \alpha_3 s_i^H + \nu_i \qquad (4)$$

where, s^L and s^H are the number of low (stereo) and high (digital) quality screens at the theater. The more general specification, reported in Column (1), models costs as quadratic in the number of stereo screens and increasing in the number of digital screens at the theater.[29]

The results do suggest that theater scale is an important determinant of construction costs. However, multicollinearity - and a lack of data at the higher screen counts - impinge upon the data's ability to distinguish clearly between constant returns to scale and increasing marginal costs of construction. Moreover, the estimate of fixed costs changes quite markedly between the two specifications, although remains a small fraction of the cost of building a large multiplex theater.

The cost of digital sound equipment is considerably less than the estimated marginal cost of building a digital screen,[30] roughly \$6,000 for DTS (Digital theater sound) and \$9,000 for SDDS (Sony Dynamic Digital Sound). Hence an appropriate interpretation of α_3 is as the costs of constructing a high quality auditorium, rather than merely converting an auditorium to digital sound. In the policy experiments

from local tax authorities.

[28]Theater costs were deflated using the standard CPI index into 1996 dollars.

[29]Initially I included other observed theater characteristics (for example the age of the theater, whether the theater had a consumer service line etc.) in equation 4. I also considered regional effects and a quadratic term in the number of digital screens. Insignificant parameter values were obtained in each case.

[30]For column (2), $\alpha_3 - \alpha_1 = \$59,509$.

	(1)		(2)	
	parameters	t_α	parameters	t_α
α_0	250204	3.1	18313	2.5
α_1	78125	1.5	146186	6.7
α_2	10068	1.6	-	-
α_3	190414	9.3	205695	11.5

Table 9: Estimated construction cost functions. Reported t statistics are calculated using heteroskedasticity consistent standard errors, White (1982). The unobserved component of costs is assumed to have a variance which increases in the observed determinants of costs: $E[\nu_i] = 0$ and, $Var[\nu_i] = \sigma * E[C_i]^2$. The model is estimated using a two-step weighted least squares (WLS) procedure. OLS on the mean equation provides consistent estimates of the parameters at the first stage and hence the appropriate weights $(E[\hat{C}_i]^2)^{-\frac{1}{2}}$ for the second stage.

reported below, I assume high quality theater auditoria are added since most new entrants do in fact build new high quality theaters.

□ **Policy Experiments.** As a representative policy experiment, below I consider the arrival of an actual sixteen screen multiplex theater built in the San Antonio, Texas, market during late 1996. As will become clear, the qualitative features of the results are completely robust to the specific circumstance considered (given the demand parameter estimates) but this actual entry provides a concrete example from which to demonstrate the forces governing product provision at work. Figure 2 shows the business stealing, market expansion, and consumer surplus gains from building new theaters of various scales, conditioning upon the decisions of previous entrants and the location and pricing decisions of the new theater. The top panel shows the market expansion effect and the business stealing effect of new product introduction. Market expansion is shown as a positive number - new products expand industry revenue - and Business Stealing as a negative number - existing theater revenue falls.

The first prominent feature of the graph shows the important effect of the availability of quality products. As noted above, product quality is assumed to increase (at a declining rate) with increases in theater scale until the maximum is reached at five screens ($f^{max} = 5$.) As the quality of films declines beyond that point, so to does the impact on rivals revenue, industry revenue, and welfare. Alternative values for f^{max} alter the point at which this maximum is reached, but little else.

Evident also from the graph is that the business stealing effect is estimated to be modest and smaller than the market expansion effect (in contrast to some previous studies such as Berry and Waldfogel (1996) who find business stealing to be substantial in radio markets.) In addition, the consumer surplus gains from new products are in turn estimated to be larger than the market expansion effect. Although the absolute numbers for each of these effects do change with the specific parameter values for $(\beta_0, \beta_1, \beta_2, \lambda_1, \lambda_2)$, this ranking is robust to very substantial variation in the parameters.

Figure 2 also demonstrates that the magnitude of each effect decreases as the linear travel cost parameter increases. As travel costs increase, markets become local and thereby *smaller*. Local markets ensure that the business stealing effect is substantially moderated as distant rival products become poor substitutes. In addition, since local markets are effectively smaller markets, the market expansion and welfare gains from new product introduction also get smaller as transport costs increase.

Figure 3 presents evidence on the optimal provision of products by a private company relative to a collusive arrangement and also relative to the welfare maximizing choices. The results are presented

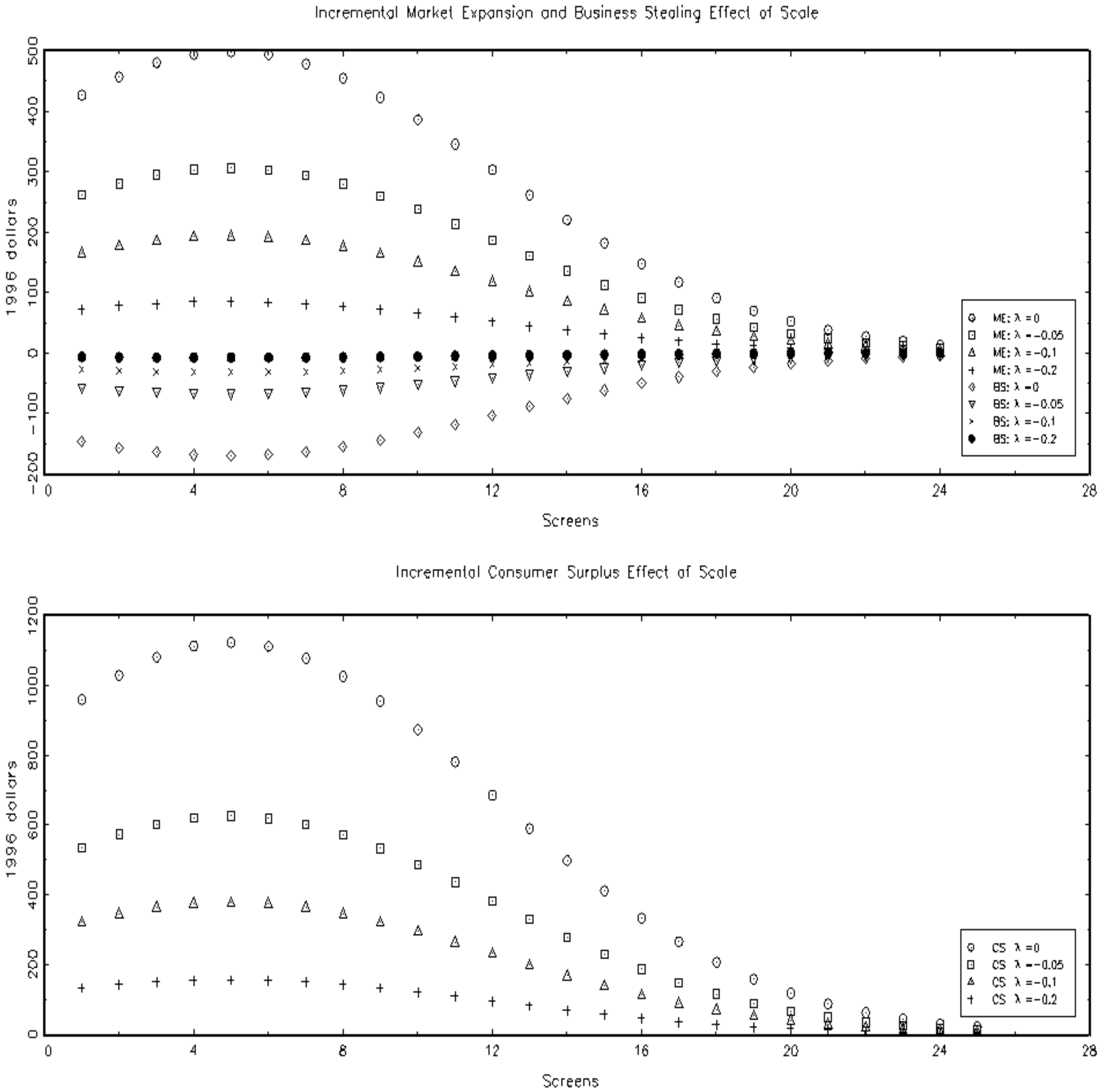

Figure 2: BS denotes the Business stolen from rival theaters: The reduction in revenue that existing rival theaters suffer from the addition of new screens. ME represents Market Expansion: The effect of extra screens on aggregate industry revenues. CS denotes consumer surplus: The incremental effect on consumer welfare of building an extra new screen expressed in dollars. All figures are in 1996 dollars and represent the respective dollar amounts for the incremental effect of extra screens on a single Friday evening. The results reported here are calculated by setting $\beta_p = -0.1$, $\beta_1 = -2f^{max}\beta_2$ with $\beta_2 = -0.01$, $f^{max} = 5$, $\lambda_1 \in \{0, -0.05, -0.1, -0.2\}$ and $\lambda_2 = 0$. Quadratic transport costs are ignored to facilitate comparison with the case where $\lambda_1 = 0$.

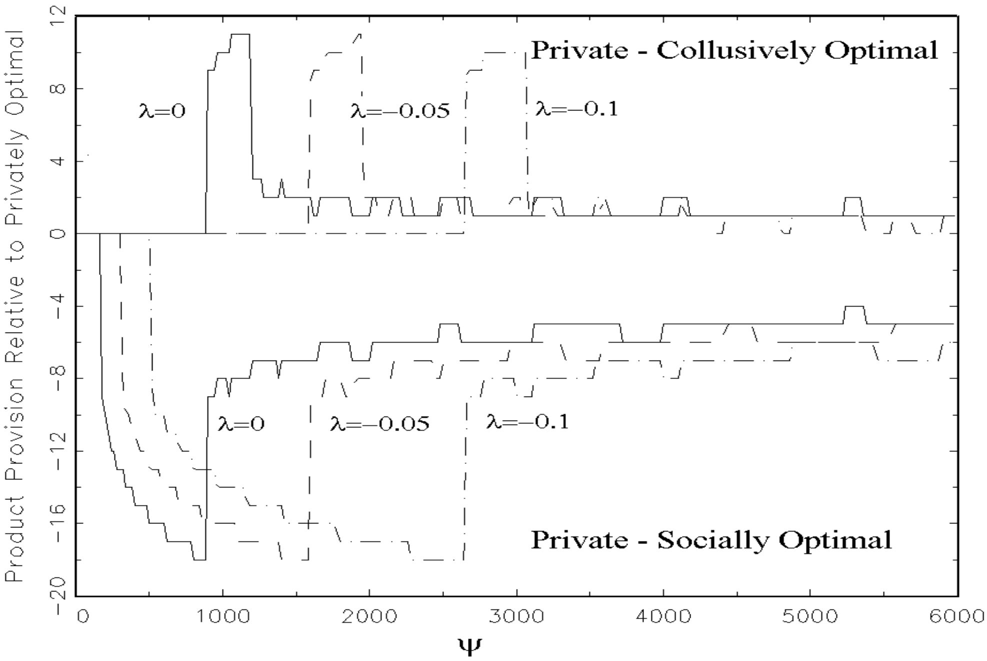

Figure 3: Single theater profit maximization yields theaters that are larger than the collusively optimal scale and smaller than the socially optimal scale.

as a function of the scale choice model's unknown parameter ψ.[31] The top half of the figure shows that the privately optimal scale is typically *larger* than the collusive scale choice. This is natural since a cartel internalizes the business stealing effect. The extent of the over provision of products under individual theater profit maximization is shown in the top half of the graph for three values of the linear transport parameter, λ_1. For small values of ψ, neither institution would introduce a new theater; their respective rewards do not cover the fixed costs of entry. At intermediate values of ψ - corresponding to the humps on the upper part of the graph - private incentives are sufficient to build the theater while a cartel would not. At larger values of ψ, both institutions build the theater.

Since the business stealing effect is estimated (and reported in the initial quotation) to be modest and decreases as marginal product quality declines, once the cartel builds the theater there are only small differences between the cartel and privately optimal theater scales. The main effect of differing transport costs on this process is clearly to change the specific values of ψ at which cartel and private entry occurs. However, a second more subtle effect is also evident at the very highest values of ψ. Namely that large transport costs reduce the difference between private and collusively optimal product provision. As transport costs increase, markets become geographically isolated and consequently the business stealing effect of introducing new products becomes negligible. [32]

The bottom half of the figure shows that the privately optimal scale is uniformly *smaller* than the

[31]The discontinuous nature of the optimal screen choice appears for two reasons. First, marginal revenues and costs are step functions. Second, marginal revenues and costs of constructing a screen are relatively flat. Consequently, small changes in ψ can result in discrete changes in the optimal number of screens.

[32]A very problematic feature of the pure logit model that is greatly reduced in the full model is that the business stealing effect of each additional new product is always non-zero however many new products get introduced.

welfare maximizing scale. Initially, fixed costs would not be covered solely by the theater's revenues, making theater profits negative. However, the substantial consumer surplus gains from new products do make it welfare enhancing to introduce new products. At intermediate values of ψ there is entry by both the planner and the profit maximizer. However, business stealing always remains relatively small and there are still un-captured consumer surplus gains which ensure under provision of products by the profit maximizing theater. Finally, notice that at the intermediate and high values of ψ, the line for $\lambda = -0.1$ lies weakly below the line for $\lambda = -0.05$ and that in turn lies below the line with $\lambda = 0$. This ranking is very natural. As transport costs increase, markets become local and the business stealing effect becomes negligible removing the incentive toward over-provision by the profit maximizer. Even in local markets, there are un-captured consumer surplus gains from new products that will accrue to the *local* population. Thus, at least some tendency for under-provision remains when transport costs are sufficiently large while the pressure toward over-provision vanishes.[33]

As a final observation on the impact of travel costs on product provision, it is worth noting what would happen if scale were interacted with distance. That is, consumers were willing to travel further to large theaters. In that case, increasing the scale of a theater for given transport cost would increase the magnitude of both the business stealing and, since the theater's market size effectively increases, the un-captured consumer surplus effects. The net effect on product provision is correspondingly ambiguous and the under-provision result will only be preserved if the business stealing effect is sufficiently small. Since I was unable to isolate these effects using the current data-set, I must defer a detailed examination of their magnitudes for future work.

The final pressure in this industry pushing the results toward under-provision is that the magnitude of the business stealing effect is reduced by the revenue sharing contracts with distributors. Those contracts ensure that theater owners capture only the fraction of the revenue from an additional screen not returned to distributors in license fees, while the social planner takes into account the full increase in consumer welfare which results from having an additional screen in place. Clearly when vertical contracts are structured to ensure revenue sharing, the usual tradeoff between business stealing and un-captured consumer surplus can be biased toward the dominance of the un-captured consumer surplus effect. Thus, the conclusion of recent theoretical work emphasizing the dominance of the business stealing effect in simple models like the logit model must be applied with great care.[34]

[33]The tendency of the logit model to perhaps over-state the welfare gains from the introduction of additional products in a non-equilibrium context emphasized by Petrin (1998) is also evident from the graph. This probably undesirable feature of the logit model drives the fact that none of the lines ever converge back to the origin. In addition, it drives the fact that the $\lambda_1 = -0.1$ line never completely converges back to the $\lambda_1 = 0$ lines for the same reason: local welfare gains from new products are never exhausted. Notably however, the tendency for the local competition ($\lambda_1 = -0.1$) to result in *more* under-provision than the pure logit model ($\lambda_1 = 0$) at intermediate values of ψ) is not a consequence of the logit assumption. Rather, it occurs directly because business stealing is estimated to be small and the local consumer surplus gains are positive. This effect would be still be present if consumer surplus gains from new products did eventually become negligible.

[34]An interesting implication of this tradeoff is that vertically integrated firms should consider a larger fraction of the business stealing revenues than independent theater operators when making theater entry and scale decisions. Thus, these results provide a possible new explanation for the trends recently observed in the industry. Specifically, the model predicts that increased vertical integration will be accompanied by more and larger movie theaters.

8 Discussion

The aim of this paper is to take a first step in the development of a framework suitable for empirically performing policy analysis in retail markets. The main methodological contribution is to show how the observed distribution of consumers, and implicitly many physical aspects of actual market structure, may easily be incorporated into an empirical model of consumer behavior in retail markets. By doing so, variation in demand between store locations can be explained partly by differences in product and store characteristics, but also by the distribution of consumers *within* the market. Crucially, the distribution of consumers also feeds directly into substitution patterns between stores.

I use the model to examine the magnitude of the business stealing and market expansion effects that result from changing theaters product characteristics and subsequently examine the scale choice of a new theater owner, in an attempt to evaluate whether firms build theaters which are too large or small relative to the socially optimal scale.

The feature of the demand model estimates that drives the results in the policy analysis section of the paper is that business stealing effects are estimated to be both small and to decline substantively as the distance between a pair of theaters increases. As a result, I find that the uncaptured consumer surplus effects outweigh the business stealing effects and consequently find that products are *under*-provided by the market. This conclusion deserves several caveats.

First, empirically Logit based models such as this one often appear to generate quite small cross-price elasticities of demand. (See for example, Nevo (2001).) To the extent that introducing geographic differentiation also acts to induce low cross price elasticities, it is possible that the under-provision results are driven by the model rather than the data. This would of course, be equally true of all theoretical work using the logit model as the base demand model before introducing geographic product differentiation. Although that fact should naturally provide little cause for confidence.

Unfortunately, in this data set I do not observe data on the revenue impact of new theaters actually expanding their scale of operation; the model is estimated using only one week of data. As a result, a formal test of the model's predictions is not possible. In future work (Davis (2002b)) I shall examine the business stealing effect more directly examining how quarterly theater revenue changes in response to new entry of theaters and the expansion of rival theaters.

Second, the policy experiments reported here are not equilibrium product introductions, but rather an evaluation of a movement away from the current status quo. All of the existing empirical literature evaluating the welfare gains from new products is of this form. In contrast, the theoretical literature has emphasized the welfare properties of symmetric (in quality and price) equilibria in differentiated product games. There are obvious opportunities for future work expanding analysis from these two polar cases, but exactly how to go about doing so remains an open question. It is one that must be answered before practical, reliable, and robust answers to these fundamentally important questions about the performance of differentiated product markets can be provided. I hope this paper provides at least a minor step along that road.

9 Appendix: Econometric Details

The sample analogues to the population moment conditions (5) are

$$G_n(\theta) \;=\; \frac{1}{n}\sum_{m=1}^{M}\sum_{h=1}^{H_m}\sum_{f=1}^{F_{mh}} \begin{pmatrix} Z_{fhm}\overline{\xi}_{fhm}(\theta) \\ \xi_{fhm2}\chi_{fhm2}(\theta) \\ \vdots \\ \xi_{fhmT}\chi_{fhmT}(\theta) \\ e_{fhm}^{demographics}(\theta) \end{pmatrix} = \frac{1}{n}\sum_{f,m,h}\psi_{fhm}(\cdot;\theta)$$

where χ_{fhmt} indicates whether observation $fhmt$ is in the dataset (taking the value one if it is and zero otherwise,)[35] $T_{fhm} = \sum_{t=1}^{T}\chi_{fhmt}$, $\overline{\xi}_{fhm} \equiv \frac{1}{T_{fhm}}\sum_{t=1}^{T}\chi_{fhmt}\xi_{fhmt}$ and $n = \sum_{m=1}^{M}\sum_{h=1}^{H_m} F_{mh}$. The generic form of the GMM estimator is (Hansen (1982))

$$\hat{\theta}^{GMM} = argmin_{\theta\in\Theta} G_n(\theta)' A_n G_n(\theta)$$

where A_n is a non-negative definite weighting matrix with rank at least equal to the dimension of θ that converges in probability to a full rank constant matrix. Under regularity conditions, the asymptotic distribution of the GMM estimator is

$$(\Gamma_n(\hat{\theta}_n)' A_n \overline{V}_n^G A_n \Gamma_n(\hat{\theta}_n))^{-\frac{1}{2}}(\Gamma_n(\hat{\theta}_n)' A_n \Gamma_n(\hat{\theta}_n)) \;\; \text{x} \;\; \sqrt{n}(\hat{\theta}^{GMM} - \theta^*) \;\underrightarrow{d}\; N(0, I_k) \text{ where } \theta \text{ is } k\text{x}1 \quad (5)$$

$$\Gamma_n(\theta) \;=\; \frac{1}{n}\sum_{m,h,f}\left[\frac{\partial\psi(\cdot;\theta)}{\partial\theta'}\right] \text{ and } \overline{V}_n^G = nVar[G_n(\theta^*)]. \quad (6)$$

Assuming independence across film, theater and market observations[36]

$$nV\hat{a}r[G] \;=\; \frac{1}{n}\sum_{m=1}^{M}\sum_{h=1}^{H_m}\sum_{f=1}^{F_{mh}} \begin{pmatrix} V_{11} & V_{21}' & V_{31}' \\ V_{21} & V_{22} & V_{32}' \\ V_{31} & V_{32} & V_{33} \end{pmatrix} \quad (7)$$

---

[35]Not all firms play every day at a given theater and the electronic and manual reporting technologies used by EDI occasionally fails so some sales data is missing. For an extensive discussion of econometric techniques for multi-dimensional unbalanced data structures in general and EDI data in particular see Davis (2002a) and the references therein.

[36]It would clearly be desirable to avoid the strong assumption of full independence across fhm. In fact, I developed an entire set of techniques for estimating the three-way error components model for unbalanced data structures, reported in Davis (2002a) to do so. Unfortunately, while the error components model could easily be estimated for a given value of the non-linear parameters, the computational burden of the error component model proved entirely too great when nested inside a search over these non-linear parameters.

where

$$V_{11} = \left(\frac{1}{T_{fhm}}\sum_{t=1}^{T}\hat{\xi}_{fhmt}\chi_{fhmt}\right)^2 Z_{fhm}Z'_{fhm}, \text{ and } V_{21} = \begin{pmatrix} \hat{\xi}_{fhm2}\chi_{fhm2}\left(\frac{1}{T_{fhm}}\sum_{t=1}^{T}\hat{\xi}_{fhmt}\chi_{fhmt}\right)Z'_{fhm} \\ \vdots \\ \hat{\xi}_{fhmT}\chi_{fhmT}\left(\frac{1}{T_{fhm}}\sum_{t=1}^{T}\hat{\xi}_{fhmt}\chi_{fhmt}\right)Z'_{fhm} \end{pmatrix}$$

$$V_{31} = \hat{e}^{demographics}_{fhm}\left(\frac{1}{T_{fhm}}\sum_{t=1}^{T}\hat{\xi}_{fhmt}\chi_{fhmt}\right)Z'_{fhm}, \text{ and } V_{33} = \hat{e}^{demographics}_{fhm}\hat{e}^{demographics'}_{fhm}$$

$$V_{22} = \begin{pmatrix} \hat{\xi}^2_{fhm2}\chi_{fhm2} & \cdots & \hat{\xi}_{fhm2}\chi_{fhm2}\hat{\xi}_{fhmT}\chi_{fhmT} \\ \vdots & & \vdots \\ \hat{\xi}_{fhmT}\chi_{fhmT}\hat{\xi}_{fhm2}\chi_{fhm2} & \cdots & \hat{\xi}^2_{fhmT}\chi_{fhmT} \end{pmatrix}$$

In these calculations sampling error in the calculation of $\mathbb{P}\{A|D_g\}^{observed}$ from the Mediamark survey is ignored since the mediamark sample consists of $20,079$ individuals which should ensure that the sampling error in raw attendance proportions is negligible. I discus simulation error extensively below.

□ **Gradient Calculations** The asymptotic distribution of the GMM estimator depends directly on the derivative $\frac{\partial\psi(\theta)}{\partial\theta'}$. The gradient can derived analytically for a subset of the parameters, denoted θ_1 since $\xi_{fhmt}(\theta)$ is linear in that subset, viz.,

$$\xi_{fhmt}(\theta) = \delta_{fhmt}(\theta_2) - \tilde{x}'_{fhmt}\beta - d_t\gamma = \delta_{fhmt}(\theta_2) - x'_{fhmt}\theta_1 \text{ where } x'_{fhmt} = (\tilde{x}'_{fhmt}, d'_t) \text{ and } \theta_1 = (\beta,\gamma), \text{ so}$$

$$\frac{\partial\xi_{fhmt}}{\partial\theta'_1} = -x'_{fhmt}, \text{ and } \frac{\partial e^g_{fhm}(\theta)}{\partial\theta} = \frac{1}{T_{fhm}}\sum_{t=1}^{T}\chi_{fhmt}\left(\int \mathbb{I}\{D_g\}\frac{\partial s_{fhmt}(\theta;\nu,L,D)}{\partial\theta}dP^*(\nu,L,D)\right)$$

where

$$\frac{\partial s_{fhmt}(\theta;\nu,L,D)}{\partial\theta_1} = x_{fhmt}s_{fhmt}(\theta;\nu,L,D) - \sum_{h=1}^{H_m}\sum_{f'\neq f} x_{f'hmt}s_{f'hmt}(\theta;\nu,L,D)$$

All other derivatives of the moment conditions are evaluated numerically inorder to construct $\Gamma_n(\hat{\theta}_n)$.

□ **Simulation Estimators** So far I have presented results that assume complex multi-dimensional integrals can easily be calculated. In fact, I follow Pakes and Pollard (1989) and McFadden (1989), who suggest using simulation estimators to approximate complex integrals. As Pakes, Berry, and Linton (2001) show, simulating the moment conditions changes the asymptotic distribution of the estimator only through the addition of one extra term required to calculate the variance-covariance matrix. Specifically, in Equation (5), $Var[G(\theta^*)]$ must be replaced by a new estimator which incorporates both an estimate of the variation in the moment conditions due to the data and also the variation due to the simulation error. These two sources of variance in the moments are orthogonal by assumption and hence the total variance of the moment conditions is $Var[G_{n,ns}(\theta^*)] = Var[G_n(\theta^*)] + Var[G_{n,ns}(\theta^*) - G_n(\theta^*)] \equiv V^G_1 + V^G_2$ where V^G_1 is simply the estimator reported in Equation (7) above and V^G_2 may be calculated by bootstrapping the moment conditions to obtain an estimate of their variance across different sets of simulation draws. Specifically, if G^r_n is the moment condition calculated using the r^{th} set of ns

simulated consumers, $\{\nu_i^r, L_i^r, D_i^r\}_{i=1}^{ns}$, then

$$\hat{V_2^G} = \frac{1}{R}\sum_{r=1}^{R}\left(G_n^r(\hat{\theta}) - \frac{1}{R}\sum_{r=1}^{R} G_n^r(\hat{\theta})\right)\left(G_n^r(\hat{\theta}) - \frac{1}{R}\sum_{r=1}^{R} G_n^r(\hat{\theta})\right)'.$$

One final computational remark is worthy of note. That is, that when calculating both $\hat{\Gamma}$ and V_1^G, the number of simulation draws are increased substantially in-order to remove simulation error from those objects. This imposes a trivial computational burden since they must each only be calculated once, after consistent estimators of the parameters have been obtained.

□ **The Linear Parameters** For a given value of the 'non-linear' parameters θ_2, the first order conditions from the GMM maximization problem are

$$\hat{\Gamma_{1n}}' A_n G_n(\theta) = 0$$

Now since $\hat{\Gamma_{1n}}(\hat{\theta_n})$ is independent of θ_1 and $G_n(\theta)$ is linear in θ_1, this provides a set of $k_1 = dim(\theta_1)$ equations which we must solve. Unfortunately, the demographic moments make this expression non-analytic since they are non-linear functions of the 'linear' parameters. Fortunately, since the k_1 linear parameters are consistently estimated from the linear moments alone, extremely good analytic starting values may be found for these parameters by first dropping the demographic moments and solving the reduced set of these equations. Specifically, construct the sub-matrix of the original weight matrix $B = A[1 : p + T - 1, 1 : p + T - 1]$ and also the sub-vector G_n' corresponding to the first $p + T - 1$ moment conditions and analytically solve these k_1 equations $\hat{\Gamma_{1n}}' B G_n'(\theta) = 0$ for $\hat{\theta}_1$.

Generically, since the 'macro' demographic moment equations help identify specific parameters in the utility of the outside good, they contain very little information about the other non-linear parameters such as distance which are common across demographic groups. Similarly, the other moment conditions provide little or no information about the composition of demand across the demographic groups. Empirically, the parameters that solve the reduced set of analytically solvable equations were universally found to be extremely close (well within even strict tolerance levels for convergence) to the parameters which solved the full set of equations.

□ **Macro-Moment Conditions.** Define $A = \{i|\text{i attends}\}$, $B = \{i|\text{i in survey}\}$ and $D_g = \{i|\text{i in demographic}$ for $g = 1, .., G$ to be the set of people who attend, are in the survey and in each demographic group respectively. We wish to calculate $Pr\{A|D_g\}$ the probability of attendance for each demographic group. Notice first that[37]

$$\begin{aligned} Pr\{A \cap B \cap D_g\} &= Pr\{D_g|A \cap B\}Pr\{A|B\}Pr\{B\}, \text{ and} \\ Pr\{A \cap B \cap D_g\} &= Pr\{B|D_g\}Pr\{A|D_g\}Pr\{D_g\}. \end{aligned}$$

Equating these two expressions and rearranging yields

$$Pr\{A|D_g\} = Pr\{D_g|A \cap B\}Pr\{A|B\}\left(\frac{Pr\{B\}}{(Pr\{B|D_g\}Pr\{D_g\})}\right) = \frac{Pr\{D_g|A \cap B\}Pr\{A|B\}}{Pr\{D_g|B\}}.$$

[37] The latter follows provided $Pr\{B|A \bigcap D_g\} = Pr\{B|A\}$ which will be true provided the sample survey design does not explicitly over-sample movie attendees beyond their demographic characteristics, which it does not.

I directly observe $Pr\{D_g|B\}$ and $Pr\{D_g|A \cap B\}$ from the survey data. Thus, it remains only to calculate the overall attendance probability of those surveyed, $Pr\{A|B\}$. Unfortunately, the Mediamark survey question asks whether the respondent has attended the movies within the last six months, while the data period is just one week. To make the survey data comparable to the revenue data, I rearrange and sum over a partition $\mathcal{P}$ of the set of attendees (such as all age groups) which implies $Pr\{A|B\} = \frac{Pr\{A\}}{\sum_{D_g \in \mathcal{P}} \frac{Pr\{D_g|A \cap B\}}{Pr\{D_g|B\}}}$. This term can be computed directly using the appropriate measure of the unconditional probability of attendance $Pr\{A\}$ constructed directly from the revenue data-set.[38]

[38]This calculation is performed separately for each demographic partition - age, income and race - in order to ensure that each sub-set of moment conditions match the revenue data appropriately.

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