Spatial Competition in Retail Markets: Movie Theaters.[1]

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Abstract

Retail markets constitute a large fraction of the economy in all industrialized countries. Yet economists know little about the way dispersed buyers and sellers affect the properties of markets. I attempt to answer several questions here. First, to what degree does geographic differentiation provide retail stores with market power? Second, what are the implications of consumer borne travel costs and business stealing, which each result in differences between private and social objectives, on store location and scale decisions.

Using new data from movie theaters I estimate a random utility discrete choice model of retail demand in which products are location specific and consumers have preferences over product characteristics. Using simulation methods I show how to incorporate data from the decennial census into an econometric model of retail demand. Census data provide a detailed description of the geographic distribution of consumers, of their demographic characteristics and, implicitly, of market topology.

I find that the cross price elasticity of demand between theaters is small and decreases with distance. Second, I identify theater re-locations which improve industry revenue and consumer welfare. Third, I use theater cost data, obtained from municipal and county building permits, to estimate an hedonic theater cost function. The combined models allow a comparison of the socially optimal and privately optimal theater size. I find that the market substantially *under*-provides 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 location ; Store scale choice.
JEL Classification: L0; L1; L2 ; L4.

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, as the final stage in the distribution channel, are inherently differentiated product markets. They also constitute 30% of the United States economy (by sales), employ 18.5 million people and provide the interface between consumers and producers for a vast number of products. The quotation above motivates several important questions for the retail sector. First, to what degree does geographic differentiation give retail stores monopoly power? Second, how do the differences between private incentives and social returns affect store location and scale decisions.

The answers to each of these questions depends upon the substitutability of retail stores. Geographic differentiation provides a retailer with monopoly power if the cross price elasticity of demand with rival stores is low or declines quickly as the distance between them increases. In contrast, business-stealing, the reduction in a rival's revenue when a firm builds additional capacity, will be large only if the new store is a good substitute for the other (Spence (1976)). The first step toward providing answers to each of these questions is therefore to develop a model of consumer demand suitable for a retail market, where products are defined by both their embodied characteristics and also by their physical locations.

The large number of products makes the traditional applied demand analysis approach, to specify consumer preferences over products, unwieldy. I follow the discrete-choice literature emanating from Lancaster (1966).[2] Discrete choice models have two components: a specification for consumer preferences and a distribution of consumers, each defined over the set of product characteristics. Endowing consumers with preferences over product characteristics solves the dimensionality problem but also requires the researcher

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

[2] If consumer preferences were defined directly over products, for example via a constant elasticity of demand system, the number of parameters to be estimated would increase with the square of number of products. For example, in the data I use from movie theaters, the 55 films playing in a given week become more than $3,000$ location specific products. Hence estimating this model would involve choosing a parameter vector from a 9 million dimensional parameter space. Projecting the product space onto a space of characteristics makes the latter the relevant dimension.

to specify (or estimate) how consumers and their tastes are distributed over the product characteristics space. The distribution of consumers and their tastes plays an important role in determining the properties of the estimated demand system. For example, Hausman and Wise (1978) and McFadden (1981) demonstrate that the assumed distribution of consumers feeds directly into the calculation of cross- and own-price elasticities of demand. Moreover, to paraphrase Spence (1976), the welfare consequences of *any* government policy or business strategy can be evaluated only relative to the distribution of purchasers. Thus, attempts to draw practical policy conclusions from convenient theoretical constructions such as the linear or circular city are correctly critiqued for their reliance on their assumptions about the distribution of consumers.[3]

However, in contrast to many product characteristics (such as the taste for quality) considerable information *is* available about the manner in which consumers are distributed over the geographic dimensions of product characteristics space. Specifically, the Census of Population (henceforth Census) provides a very detailed non-parametric estimate of the geographic distribution of consumers and their demographics within a market. I demonstrate how to estimate a model of demand for differentiated products which directly incorporates the distribution of consumers observed by the Census. Thus, once the parameters of the model are estimated, policy analysis is performed relative to the best available guess of the *actual* distribution of consumers.[4] Moreover, by developing the empirical analogue to the theoretical models of demand in retail markets, many of the issues which have proven problematic for location analysis are easily addressed. For example, whether transport costs are appropriately modeled as linear or quadratic functions of distance is just an empirical question which may simply be determined from the data.

I use the estimated model to examine the location and scale incentives facing retailers in the motion picture theatrical exhibition market, i.e., movie theater owners. The movie exhibition market provides a nice environment in which to study retail markets, since exhibitors stock only a small number

[3]See Hotelling (1929), Salop (1979), d'Aspremont, Gabszewicz, and Thisse (1979), and most recently Ansari, Economides, and Steckel (1998) and Irmen and Thisse (1998).

[4]de Palma, Lindsey, von Hohenbalken, and West (1994) calibrate a model of retail demand using the distribution of consumers provided by the census to illustrate the problems emphasized by Eaton and Lipsey (1975), Spence (1976), and Okabe and Aoyagi (1991). Namely, that geographical features such as the shape of the market and the distribution of consumers materially affect the welfare properties of location games.

of well defined, non-transportable, and non-storable products. As I shall describe below, the exhibition market also operates relatively independently from the distribution market as compared to most retail markets. Moreover, the film industry uses a private company called Entertainment Data Inc. (EDI) to collect and disseminate revenue information for each film playing at each theater. Thus, the movie exhibition market provides a rare instance in which price and sales data are available for each location specific product.

The plan of this paper is as follows. First, I describe the history and institutional structure of the exhibition market. Section 3 describes the demand modeling framework, while section 4 describes the new data set. Section 5 presents estimates of the demand side parameters used in Section 6 to examine the implied relationship between cross price elasticity and distance between stores. Section 7 considers what happens to industry revenue and consumer welfare as a single theater is relocated within the market. Section 8 presents estimates of the construction cost function for movie theaters. In section 9, I combine the supply and demand models and consider their implications for the incentives for store scale decisions in retail markets. I also quantify asymmetries in business stolen from rivals by a new entrant. Finally, I conclude and outline directions for future research.

2 The Movie Exhibition Market

The movie industry began when America's most famous inventor, Thomas Edison, patented his motion picture camera in 1889.[5] The first cameras allowed only a single person to view the film by means of a peep show. In 1895, Auguste Lumière presented the first movie projector, the Cinématographe, and only seven years later the first dedicated movie theater, Los Angeles' Electric Theater, opened. Between 1895 and 1902, film lengths grew from 50 feet to more than $1,000$, with a screen time of up to 15 minutes.

During the next few years, Edison attempted to monopolize the industry by controlling access to movie technology. The resulting acrimony ended in 1908 when the studios agreed to combine their patents to form a cartel, the

[5]For detailed description of the history of the industry, see for example Balio (1985) or Kindem (1982). For a re-evaluation of early antitrust actions see Conant (1960). The volume edited by Squire (1992) provides a comprehensive description of present business practices.

Motion Picture Patents Company. In addition, to counter rivalry from new independent producers,[6] the studios integrated vertically into theaters and created the General Film Company.[7]

Despite several successful anti-trust actions, including one in 1918 which dissolved the General Film Company, in 1939 the five major film producer-distributors[8] owned or controlled all but 37 first run theaters in the largest twenty five US cities. In the landmark case of U.S. v. Paramount et al. (1948),[9] the Supreme Court found the five majors guilty of restraint of trade, including vertical and horizontal price fixing. Following the decision, the courts ordered the vertical disintegration of the industry. Moreover, the divorced circuits were required to divest themselves of approximately one half of the 3,000 or so theaters they owned. Today, the most controversial element of the consent decrees remaining in force requires that films be licensed on a theater-by-theater basis, on the merits.[10] Whatever the merits of the case to keep or remove the strictures imposed by the Paramount decrees (see for example De Vany and Eckert (1991) for a case to remove), the implication is that distributional arrangements are somewhat uniquely arms-length for a retail market, a feature of the industry simplifying my analysis considerably.[11]

Almost immediately after the Paramount decrees came widespread ownership of televisions. The number of homes owning TV sets jumped from 4 million at the end of 1949 to 42 million in December of 1957, representing a jump from only 12% of homes with TV sets to 86%. At the time, cinema and television were competing head to head for news as well as entertainment. Theater attendance fell by 42%, while the total number of screens fell from 18,631 in 1948 to a low of 12,652 in 1963.

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[6] Many of whom produced films in Los Angeles (Hollywood) where they could be close enough to the Mexican border to flee prosecution for patent infringement if necessary.

[7] General Film forced the sale to it of 57 of the 58 principal film exchanges and drove the small ones out of business by refusing to sell them films. William Fox owned the one principal exchange that refused to join the pool, he entered production, and expanded his distribution network nationally.

[8] Paramount, Warner Brothers, 20th Century Fox, Loew's, and Radio Keith Orpheum.

[9] United States v. Paramount Pictures, et al., U.S. 334 US 1.

[10] Some provisions of the consent decrees have recently been shelved. In particular, film producers are now allowed to operate theaters again and some limited bundling of films is now allowed. However, most restraints remain in place.

[11] Moreover, the coordinating task facing movie theater owners, to obtain a single roll of film for each screen every few weeks, is trivial relative to even a small supermarket which must manage the delivery of thousands of Stock Keeping Units (SKU's) each day.

Theater operators survived the introduction of TV by successfully differentiating the experience of seeing a film on the big screen from that offered by television. Immediately following the arrival of TV, producers made much more widespread use of color, depth, and techniques like Cinema-Scope which required wider screens and other new experience-enhancing technologies. This strategy of differentiation significantly reduced the impact of the subsequent introduction of VCR's and, more recently, cable, satellite and pay-per-view TV.

The exhibition market is now a small but culturally important retail business grossing roughly \$6.3 billion in annual sales during 1997. In contrast to the national distribution market, where the eight major players still account for over 95% of sales, the top five exhibitors account for only 41% of the approximately 32,000 screens in the U.S. However, fragmentation at the national level masks high market concentration. Table 5 shows one-firm concentration ratios are as high as 77% in medium sized markets such as Portland, Oregon.[12] Moreover, the trend in the industry is toward consolidation and vertical integration. The most recent examples include the highly contested merger between Sony Theaters and Cineplex Odeon[13] and the takeover by the leveraged buyout (LBO) firm KKR of both Regal Cinemas and ACTIII.

At the theater level, the most dramatic trend is the increasing size of the multiplex (multi-screened complex). This trend is illustrated in Figure 6, which shows the evolution in theater size over time. The first round of multiplex theaters partitioned existing theaters. Now, many new theaters open with ten or more screens while the largest theaters in operation have as many as 30 screens. Table 6 shows the distribution of the number of screens per theater in this dataset. Only 20% of screens are in theaters smaller than the modal size of six screens.

3 Components of a Demand System

I model demand using a discrete choice differentiated product, differentiated consumer, framework. Following Lancaster (1966), agents are endowed with

[12] I postpone a full discussion of the data until Section 4. However, one feature of this market level data worth noting is the lack of correlation between measures of market concentration and adult admission prices.

[13] Sony and Cineplex were forced to divest several theater holdings in both New York and Chicago before the merger was approved by federal regulators.

preferences over product characteristics and choose that product whose characteristics maximize utility given the set of available alternatives.[14] Modeling the demand for product characteristics in this fashion, rather than for the products themselves, ensures that consumers substitute between products with similar characteristics.[15]

Consumer preferences are assumed to vary systematically with consumer characteristics: consumers with similar characteristics will therefore tend to purchase similar products. Specifying the distribution of consumer characteristics, including their location, completes the model. Demand for each product is the sum of all consumers who chose to buy that product given all the products characteristics, the specification of preferences, and the distribution of consumer characteristics. Methodologically, the contribution of this paper is largely in the treatment of the geographic dimensions of consumer characteristics. First, I specify a model of preferences.

3.1 Consumer Preferences

I observe $t = 1, \cdots, T$ days of sales data for each film $f = 1, \cdots, F^{ht}$ in each theater (house) $h = 1, \cdots, H^m$ for each of $m = 1, \cdots, M$ markets. For clarity of exposition, I omit the time and market subscripts except where necessary.

A product is a film at a specific theater. Thus, the indirect utility consumer i obtains from watching film f at theater h is

$$u_{ifh} = x'_{fh}\beta_i^* - \alpha_i^* p_{ih} - g(d(L_i, L_h); \lambda_i^*) + \xi_{fh} + \epsilon_{ifh} \tag{1}$$
$$i = 1, ..., I, f = 1, ..., F^h, h = 1, ..., H.$$

where $(\alpha_i^*, \beta_i^*, \lambda_i^*)$ are individual specific coefficients, x_{fh} are K_1 observable

[14]A recent survey (Daily Variety, October 22nd 1998, p1.) reports that 94% of movie goers choose which film, and necessarily which theater, to attend before arriving at the theater. Hence a model of rational choice from the set of available alternatives provides a good description of the actual choice behavior demonstrated by consumers in this market.

[15]An alternative is to group products into market segments and use Gorman (1971)'s multi-stage budgeting approach: consumers first choose a market segment, then a product within the chosen segment. See Hausman, Leonard, and Zona (1994) who use a flexible functional form (Deaton and Muellbauer (1980)'s Nearly Ideal Demand System) for demand within segment. Unfortunately, this approach is infeasible since there is no obvious way to geographically segment the market. See Hausman (1994) for a discussion of the benefits of the segmentation approach.

product characteristics, p_{ih} is the price for individual i at theater h and $d(L_i, L_h)$ is the distance from the consumer's location L_i to the theater's location L_h and $g(\cdot,\cdot)$ is a function such as a linear or quadratic function, known upto the (K_2x1) vector of parameters λ_i^*. ξ_{fh} represents an unobserved (by the econometrician) product characteristic and ϵ_{ifh} is a mean zero individual and product specific stochastic term.

Examples of observed product characteristics are: 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. Film characteristics include genre and the film's aspect ratio, however film fixed effects can also be used. The unobserved product characteristic is observed by, and common to, all individuals. Hence, at equal prices and differences, all consumers prefer a high ξ_{fh} product. I assume that both firms and consumers observe all the product characteristics and take them into account when making decisions.

3.2 Consumer Characteristics

Traditionally, to estimate a model of demand for location specific products, a researcher would need survey data giving individuals attendance decisions, prices, measures of the distance traveled and other consumer characteristics. (See for example, McFadden (1981) or Goettler and Shachar (1997)). Unfortunately, performing consumer surveys is extremely expensive, and consequently consumer level data is rarely available.[16] Instead, where possible, I use the observed distribution of consumer characteristics directly. The decennial Census of Population provides us with a non-parametric estimate of the geographic distribution of consumers within a city, their age, income and race.

The consumer characteristic at the center of this study is geographic 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 nests both the linear and quadratic transport

[16] Some researchers have resorted to calibration to circumvent the lack of survey data (Fotheringham (1988)). More recently scanner data has provided new consumer level choice data. Even scanner data is unlikely to provide an easy solution to this problem because while coverage within a store is usually good, coverage across stores is frequently incomplete.

cost specifications used by Hotelling (1929) and d'Aspremont, Gabszewicz, and Thisse (1979) and determining which is relevant becomes an empirical question (I find significant non-linearities, although not precisely of the form usually considered in quadratic transport cost models.) Many notions of distance could be used. For simplicity I use Euclidean distance so that a consumer's indifference curves in geographic space are concentric circles about her location.[17] 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.

Typically, there remains some heterogeneity in tastes for product characteristics about which we have very little information. For example, the correct distribution to describe heterogeneity in consumer tastes for store quality, or theater sound, is difficult to specify a priori.[18] Assuming that the distribution is known up to a parametric family, I model the variation in tastes across consumers as a multivariate normal distribution with a mean that is a function of the consumers demographic variables and parameters to be estimated (following Berry, Levinsohn, and Pakes (1995) and Nevo (1998)). Define

$$\gamma_i^* = (\alpha_i^*, \beta_{i1}^*, ..., \beta_{iK_1}^*, \lambda_i^*), \text{ and } \gamma = (\alpha, \beta_1, ..., \beta_{K_1}, \lambda)$$

where K_1 is the number of observed product characteristics, and let

$$\gamma_i^* = \gamma + \Pi D_i + \Sigma^{1/2}\nu_i, \quad \nu_i \sim N(0, I_{K_1+K_2+1}) \tag{2}$$

Where D_i is a dx1 vector of demographic variables, Π is a (K_1+K_2+1)xd matrix of coefficients which measures how the taste characteristics vary with

[17] 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. 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 drop to 0.826 for distances below 15 miles. For trips below 15 miles, travel time per mile is generally greater than for longer distances.

[18] As I noted in the introduction, welfare conclusions from these models are all relative to the assumed distribution of consumers over product characteristics, which we have little a priori information. See Petrin (1998) for a discussion of how policy conclusions may be affected by assumptions about the distribution of consumer tastes.

demographics, and Σ is the covariance between an individual's unobserved component of tastes which may also be estimated. In the results below, demographic variables include age, income, and race.

Unobserved heterogeneity across consumers plays two important roles. First, each consumer is endowed with a different marginal utility from an observed product characteristic, thus the model allows consumers to react differently in response to, say, a price change. Second, for a given individual, the marginal utility available from each product characteristic is constant across alternatives. The desirable implication is that each individual finds that products with similar characteristics are better substitutes. See Hausman and Wise (1978) and Berry, Levinsohn, and Pakes (1995) for extensive discussions of the implications of correlation induced by unobserved heterogeneity.

Some consumers decide not to attend any screening of a film, instead consuming their "outside option." The indirect utility from the outside option is

$$u_{i0} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \epsilon_{i0}. \tag{3}$$

Without this feature, 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. As usual with this kind of model, the mean utility of one good is not identified because multiplying the utility of all goods by a constant does not change the individual's choice. Consequently, I choose to normalize ξ_0 to zero.

For both exposition and computation, it is useful to separate u_{ifh} into two components: a component common to all consumers and a component which differs across consumers. Denote the utility every consumer derives from consuming film f at theater h, δ_{fh}. Under this utility specification,

$$\delta_{fh} = x'_{fh}\beta + \xi_{fh}. \tag{4}$$

Let $\theta = (\theta_1, \theta_2)$ be a vector containing all the parameters of the model, where $\theta_1 = (\beta_1, ...\beta_{K_1})$ are the parameters from Equation 4 and

$$\theta_2 = (\alpha, \lambda, \Pi, \Sigma, \pi_0, \sigma_0)$$

are parameters on variables whose contribution to utility differs across individuals.

Consumers attend at most one film at a single theater, that which provides the highest utility. I do not observe the individuals' choices directly; rather the model implicitly defines the set of consumers who choose film f at theater h:

$$A_{fh}(x,p,\delta;\theta_2) = \{(L_i, D_i, \nu_i, \epsilon_{ifh}) | u_{ifh} > u_{igl} \ \forall g,h,f,l \text{ s.t. } (h,f) \neq (g,l)\}$$

where x are the characteristics of all the theaters, $p = (p_{11}, p_{12}, \cdots, p_{HF})'$, $\delta = (\delta_{11}, \delta_{12} \cdots, \delta_{HF})'$ and $(L_i, D_i, \nu_i, \epsilon_{ifh})$ are unobserved consumer characteristics.

The market share of film f at theater h is the sum of all consumers who choose that option. Because consumers consider all the available options before making a choice, market shares are a function of the characteristics of all the $\sum_{h=1}^{H} F^h + 1$ goods in the choice set. Assuming each individual is indifferent with probability zero,

$$\begin{aligned} s_{fh}(x,p,\delta;\theta_2) &= \int_{A_{fh}} dP^*(L,D,\nu,\epsilon) \\ &= \int_{A_{fh}} dP^*(\epsilon) dP^*(\nu|D,L) dP^*(D|L) dP^*(L) \qquad (5) \end{aligned}$$

where $P^*(\cdot)$ denotes a population distribution function. The second equality follows from Bayes rule and the assumption that the logit error is independent of an individual's other unobserved characteristics $P^*(\epsilon|\nu,L,D) = P^*(\epsilon)$. In contrast to the previous literature, the distribution of consumer demographic characteristics are observed at many places within the broad market area and information is used on the distribution of consumers across the market.

The integral in Equation (5), which defines a product level demand curve, is taken with respect to four unobserved components, $(L_i, D_i, \nu_i, \epsilon_{ifh})$. These consist of variables which are potentially available from survey data, (L_i, D_i), and others which are unobservable (ν_i, ϵ_{ifh}). The most tractable model, that used by most of the discrete choice literature using consumer level data,[19] is obtained by assuming $d(L_i, L_h) = 0$, $D_i = 0$, and $\nu_i = 0$ so that individuals are different only through the additively separable random term, ϵ_{ifh}.

This corresponds to the conditional multi-nominal logit (MNL) model if ϵ_{ifh} is distributed *i.i.d.* across individuals and choices with a Type I extreme value distribution. The probability that an individual with given observable

[19] Goettler and Shachar (1997) and Berry, Levinsohn, and Pakes (1997) are exceptions.

characteristics attends a film at a given theater becomes

$$s_{ifh} = \frac{exp(x'_{fh}\beta_i - \alpha_i p_{ih} - g(d(L_i, L_h); \lambda_i) + \xi_{fh})}{1 + \sum_{g,l} exp(x'_{gl}\beta_i - \alpha_i p_{il} - g(d(L_i, L_g); \lambda_i) + \xi_{gl})}. \tag{6}$$

If only product level data is available, the MNL model requires that all consumers differ only according to the logit error. Thus, consumers pay the same admission price $p_{ih} = p_h$, $\alpha_i = \alpha$, $\beta_i = \beta$ and $\lambda_i = 0$ for all i. The model implied by these assumptions does have an attractive simplicity, but its most frequent employment is as a useful, albeit at this point straw, opponent to develop the virtues of a more general model. It is well understood to restrict substitution patterns so that they depend only upon market shares (differentiate the log of the restricted function with respect to p_h or p_l). In the context of movies, this implies that if two theaters have similar market shares, the substitution from a third theater toward either of them will be the same, irrespective of its proximity or the films playing. The inability to include consumer heterogeneity, other than through the additively separable random term, means that consumers exist only in a single place, there is no third degree price discrimination, and consumers are homogeneous in their intensity of tastes for product characteristics.

Consumer level survey data allows the model's parameters, and hence substitution patterns, to depend upon individuals' characteristics. Although any random sample of consumers permits estimation of the consumer's conditional demand function, Equation 6,[20] only a representative random sample of individuals allows aggregation to the product level demand curve, the object of interest (Equation 5).[21] Hence, to calculate product level substitution patterns, the distribution of unobserved consumer characteristics $P^*(\epsilon, \nu, L, D)$ must be specified.

This suggests a more direct approach which requires only product level data. Given a specification for the distribution of unobserved consumer characteristics, computing product level demand requires only the calculation of an integral. Generally, neither the distribution nor the integral will have an analytic closed form. However, simulation techniques provide a practi-

[20] For example, via maximum likelihood.

[21] More accurately, knowledge of the sample selection process is required. Berry, Levinsohn, and Pakes (1997) for example, use data from a large survey to estimate the consumer level demand curve and subsequently model the sample selection process to derive the product level demand system.

cal solution to the problem of aggregating from consumer to product-level demand. (See below for more details). The use of simulation to solve aggregation problems was first proposed by Pakes (1986).

Using simulated consumers drawn from the true distribution of consumers the model retains the desirable substitution patterns usually provided by survey data without the need to undertake a survey. Specifically, the substitutability of any pair of products will vary with demographic and taste characteristics. Moreover, by allowing the distribution of the population to vary within the market, substitution patterns will depend on the location of consumers vis à vis stores. (See figure 8 for an illustration.)

In contrast to the product-level MNL model, the variation in market shares within and across cities does not need to be explained solely by variation in theater characteristics, films offered and market level variables. Variation in observed market shares between films and, more importantly, between the same film at different theaters and in different markets identifies the parameters of the distribution of consumers tastes and observable characteristics. I follow Berry, Levinsohn, and Pakes (1995) assuming a parametric functional form for the distribution of unobservable tastes.

The distribution of observable components of consumer heterogeneity are typically obtained from an existing database. For example, Berry, Levinsohn, and Pakes (1995) obtain the distribution of income in the United States from the Current Population Survey (CPS), while Nevo (1998) retrieves market level demographics from the same source and Petrin (1998) obtains consumer level data from the Consumer Expenditure Survey. Estimation of the model considered here requires detailed information on the distribution of consumers locations and demographics *within* each market. I use the non-parametric estimate of the joint density of consumer demographics and locations (age x income x race x location) within a market provided by the decennial Census of Population. (See below for more detail.)

3.3 Consumer Location and Demographics

The Census of Population (1990) provides a detailed picture of the geographic distribution of consumers and their characteristics within each market. The Census Bureau partitions every county in the US into census tracts. For example, Figure 10 shows a map of the census tract boundaries for the market area in Nashville, Tennessee. Each tract usually contains between three and eight thousand people.

	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%.

The Census then reports population characteristics within the tract for some $3,500$ data objects. Unfortunately, most of these data objects describe marginal densities, whereas to simulate consumers with multiple characteristics, the joint density of those characteristics is needed.[22]

An estimate of the joint distribution of age and income by race is reported. Table 9 describes the average, over all $9,506$ census tracts partitioning the 36 markets, of the observed joint distribution of age and income. Notice however, that the census reports an estimate of the joint distribution. The Census Bureau constructs a random sample of census returns in each tract and reports the required joint distribution of age, income, and race within the census tract.[23]

Denote this joint density $F(a, y, r|L)$ where L denotes location, as before, and $D = (a, y, r)$. Table 1 describes the census tract data in detail. Evidently, the census also provides $F(L)$, the probability that an individual drawn at random from the population will live in the census tract. To simulate the

[22] An estimate of the joint density of most of the $3,500$ data objects is available at the county level of aggregation in the Public Use Micro-sample. In principle, at least, an estimate of the joint density of any pair of tract level variables could be constructed by combining the county level information with the tract level marginal densities.

[23] 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.

integral in Equation (5), i.e., demand, I draw a random sample of size ns from the joint distribution, $F(a, y, r, L)$.[24]

To calculate the distance a consumer travels to each theater we must specify a location, a longitude and a latitude, for each individual.[25] A number of alternative treatments are possible, but for simplicity I choose to locate all consumers within a census tract at the tract's central point.[26]

4 Data

The data required to consistently estimate the demand model, in addition to the census data described above, consist of the following variables: market shares for each film at each theater in each market, theater characteristics (including admission prices and theater locations), and film characteristics.

Daily box office receipts were obtained from the Entertainment Data Inc. (EDI) database in Beverly Hills. These data are collected by EDI electronically overnight and are made available in real time via an online service to which theater owners and distributors subscribe. 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.[27] Indepen-

[24] To sample from an individual from an arbitrary univariate distribution $F(\cdot)$, function I use the standard inversion technique. First draw u from the Uniform distribution $U[0, 1]$ and compute $v = F^{-1}(u)$. The resulting random variable V has the required distribution, $F(\cdot)$. This technique is easily adapted to draw from an arbitrary distribution function by using Bayes rule. First, choose the consumer's home census tract, L, by drawing from $F(L)$. Next, pick an individual with race r from the conditional cdf, $F(r|L)$. Similarly we select her age from $F(a|r, L)$ and finally her income by inverting $F(y|r, a, L)$.

[25] A point, x, on the Earth's surface is described by it's latitude and longitude, expressed in radians $x = (x_1, x_2) = (latitude, londitude)$. The distance between any two points, x, y may then be computed using the expression $distance = 3963 * arctan\sqrt{\frac{1-c^2}{c}}$, where $c = cos(x_1) * cos(y_1)(cos(y_2 - x_2)) + sin(x_1)sin(y_1)$ and 3963 is the Earth's radius in miles (Maling (1992)). Although taking into account the curvature of the Earth in this way is unlikely to make a substantive difference to the results, it is also clearly very simple to do.

[26] An alternative is to distribute consumers uniformly within each tract. Unfortunately, the irregularity of the census tract boundaries (they are often non-convex sets) makes this assumption computationally burdensome to implement because each simulation draw would require the solution of a point in polygon algorithm. An easy, *point in polygon*, algorithm does exist to solve this program, hence it could be utilized in future work.

[27] In 1996, these eleven distributors accounted for 96% of box office revenue; National

dent 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 online service for flash reporting which, in turn, is used to guide advertising and promotion expenditures. EDI aggregates sales data across screenings, so matinee and evening performances are lumped together, and also across consumer types, so we observe one sales figure for each film at each theater. Daily sales data from 36 U.S. cities for one week (June 21^{st} - June 27^{th}, 1996) were obtained.[28] Unfortunately, budget constraints prevented the use of a longer time series.

Market shares are defined by converting box office grosses into attendance (dividing by adult evening admission price) and expressing attendance as a fraction of the market population. Tables 10 and 11 present summary statistics from the sales data. Approximately one in one hundred and fifty people attend the movies each evening, with Saturday the most popular evening, closely followed Fridays and Sundays.

Next, I constructed a theater atlas consisting of cinema addresses for each market in the sample using newspapers, telephone directories, and the Internet.[29] I geocoded (attached longitudes and latitudes) the addresses using the *PhoneDisc Powerfinder Pro* phone book on CD-ROM. During the summer of 1996, I undertook a telephone survey of each theater in the sample (873) to elicit admission price schedules and theater level characteristics such as the number of stereo sound systems, digital houses, THX auditoria, whether the theater was handicap accessible, had devices for the hearing impaired and a

Association of Theater Owners (N.A.T.O. (1998)).

[28] The markets were chosen by decidedly pragmatic criteria. Initially I attempted to collect the data for a larger sample, of about 60 US cities. These cities were those for which local newspapers could be obtained in New York from specialist news-agents (one appropriately called "Hotellings.") The largest markets were removed when collecting data on theater characteristics proved impractical. A second round of cities were removed as a result of various data limitations, primarily when EDI did not receive data from an important regional theater circuit. EDI report theater coverage is approximately 97% of first run theaters. Table 7 reports sample coverage in this sample of markets using screen counts for both first and second run screens. Coverage based upon fraction of revenues would be considerably higher.

[29] A huge debt of gratitude is due to a long list of friends, friends of friends, and friends of friends of friends living in each city who contributed to making this atlas as complete as possible. EDI sell this information to theater owners and distributors but direct purchase of this information proved impossible with EDI's pricing scheme.

Variable	Mean	S.D.	Min	Max	variation
Theatres	17.08	11.52	2.00	50.00	-
Screens	134.42	83.25	17.00	402.00	89.7%
Stereo Screens	79.60	46.02	4.00	203.00	90.3%
Digital Screens	26.89	25.02	0.00	131.00	90.5%
THX Screens	5.47	7.96	0.00	34.00	10.9%
Drive In's	1.39	1.57	0.00	7.00	94.0%
Pub Cinemas	0.42	0.81	0.00	3.00	92.3%
Adult Prices	4.96	0.44	3.81	5.81	88.1%
Children's Prices	3.39	0.40	2.65	4.50	87.0%
Senior's Prices	3.16	0.41	2.40	4.50	84.7%
Consumer Service line	0.73	0.14	0.41	1.00	89.1%
Handicap Accessibility	0.74	0.13	0.44	1.00	92.3%
Hearing Impaired	0.53	0.13	0.21	0.81	89.8%

Table 2: Variation in theater characteristics across markets.

consumer service line.[30] In the estimation results reported below, a match between the EDI sales data and the theater survey data was found for 612 of the 873 theaters.

Table 4 presents summary statistics describing market level variation in theater characteristics obtained from the telephone survey. The average market in the sample has seventeen theaters with a combined 134 screens and the average price of admission is $4.96. The distribution of prices in the industry is bimodal, with lower price second-run theaters and higher priced first run theaters.[31] The final column shows the fraction of variance across markets. For all theater characteristics, except the number of THX auditoria, there is relatively little variation within a market. Hence almost all the variation in sales across theaters within a market for a particular film occurs as a result of either unobserved film and theater characteristics or differences in the

[30]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.

[31]Almost no one actually pays the average admission price ubiquitously used by previous demand studies and used by the Bureau of Labor Statistics to calculate inflation in the industry.

distribution of consumers and their characteristics.

Finally, film characteristics were obtained from the Internet movie data base[32] and verified using newspaper and online film reports and reviews. Observed film characteristics are reported in Table 8.

4.1 The Estimation Algorithm

In this section, I outline an estimation strategy. The methodology presented here follows Berry (1994) and Berry, Levinsohn, and Pakes (1995) who construct a generalized method of moments (GMM) estimator which consistently estimates the parameters of both the full model and, as a very special case, the product level logit model.

Essentially, the idea is to make an intuitive, identifying, assumption; that the unobserved product characteristics, ξ_{fh} are uncorrelated with a set of instruments, denoted $Z = [z_1, \cdots, z_p]$, at the "true" parameter value, θ^* Formally, the population moment restriction and its sample analogue are given by the expressions

$$E[Z_{fh}\xi_{fh}(\theta^*)] = 0 \tag{7}$$

$$G_n(\theta) = \frac{1}{\sum_{h=1}^{H} F^h} \sum_{h=1}^{H} \sum_{f=1}^{F^h} Z_{fh}\xi_{fh}(\theta). \tag{8}$$

The GMM estimate is defined as the value of the parameters which minimizes the distance between the sample analogue to the population moment condition and zero:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \quad ||G_n(\theta)||_A \tag{9}$$

where $||x||_A = x'Ax$. The weighting matrix A may be any symmetric, positive definite, matrix, however for efficient estimation, A is a consistent estimate of $(E[\xi_{fh}^2 Z_{fh} Z_{fh}'])^{-1}$ (see Hansen (1982)).

An alternative formulation would define the model's error term as the difference between observed and predicted market shares. This option is rejected because market shares are highly dependent observations. Rather, the unobserved product characteristics ξ are obtained by a two step procedure.

[32]http://www.imdb.com

The first step is achieved by solving for δ in the set of implicit equations that equates the observed market shares to the predicted shares. Thus,

$$s_{fh}(\delta; \theta_2) = s_{fh} \forall\ f, h$$

In some cases (eg., the logit model), this equation can be solved analytically. However, for the full model suggested above, it must be solved numerically. Berry, Levinsohn, and Pakes (1995) prove a contraction argument to establish that iterating the equation

$$\delta^r = \delta^{r-1} + log(s_{fhmt}(\delta^{r-1}; \theta)) - log(s_{fh}) \tag{10}$$

solves the system above, making computation fast and simple.

Having inverted the market share function, the unobserved product characteristic is defined using Equation 4.

$$\xi_{fh} = \delta_{fh}(s, \theta_2) - x'_{fh}\beta \tag{11}$$

In Equation 11, ξ is a linear function of the parameters in θ_1, so that the minimization problem (9) may easily be solved analytically for those parameters. Consequently we need only numerically minimize the function above over θ_2, the non-linear parameters. Dividing the minimization problem into two components reduces the dimensionality of the minimization problem considerably because the empirical specification includes market, time, and for some specifications film specific dummy variables which enter Equation 11.

4.2 Moment Conditions and Instruments

The key identifying assumption in the algorithm presented above is Equation 7. However, in some of the specifications below I also utilize a second set of moment conditions from industry level survey data. These second set of moment conditions are not required for consistent estimation but improve the precision of the estimates. Specifically, I use data collected annually by the Motion Picture Association of America (MPAA) to determine national audience demographics and require the model's prediction of aggregate consumer demographics to be close to the observed demographics of attendees obtained from the MPAA survey data.[33]

The results I present here restrict the age distribution of consumers, the only demographic variable reported in the public version of the survey. Let $Age[a,b)$ be the set of consumers with age in the half open interval $[a,b)$, and let $\sum_{fh} s_{fh}^{Age[a,b),observed}$ be the observed fraction of the population who are in that age group and whom attend a theater. Each age group $\{[0,25),[25,60),[60,\infty)\}$ provides a moment restriction, by matching the model's prediction of the probability of attendance conditional upon age group.[34]

$$E[\sum_{fh} s_{fh}^{Age[a,b)}(x,p,\delta;\theta^*)|Z] - \sum_{fh} s_{fh}^{Age[a,b),observed} = 0 \tag{12}$$

In order to use the moment conditions provided by Equations 7 and 12 I need to specify a set of instruments, Z. As is usually the case in product level demand studies, a large number of potential instruments are available because the characteristics of all products in the market affect the demand for any individual product. Assuming that the unobserved characteristic of a product is uncorrelated with observed characteristics of its rivals, all rivals' product characteristics provide valid instruments. Moreover, all own theater and film characteristics which are uncorrelated with unobserved theater quality are also valid instruments.

To capture all the information in the available instruments optimally and succinctly, we would like to evaluate at least an approximation to the optimal instrument set.[35] First, consider estimating the linear parameters in

[33]In addition, I attempted to obtain data on consumer characteristics from the consumer expenditure survey (CEX). Unfortunately, the CEX aggregates live theater and movie theater expenditures, while important demographic variables (eg., age) are likely to enter preferences in dramatically different fashion across the two markets.

[34]The MPAA survey provides the distribution of consumers ages conditional upon attendance: $(0.355, 0.525, 0.12)$, so that 35.5% of theater goers are under the age of 25 while 12% are over sixty. In contrast, the moment condition is based upon the opposite conditional probability: age group given attendance. Since we also observe both the marginal distributions of age and attendance, the latter is easily calculated using Bayes rule: $Pr\{Attendence|Age\} = Pr\{Age|Attendence\} * Pr\{Attendence\}/Pr\{Age\}$. While a more detailed description of the age distribution of attendees is available from the M-PAA data, the survey data corresponds to data about individuals while the census data corresponds to data on households. For that reason, I used only three broad categories.

[35]Equation 7 defines a non-parametric model since we have not specified the whole distribution of $\xi.Z$ up to an unknown parameter, only that its mean is zero. Consequently,

Equation 11. Chamberlain (1987) proves that the optimal instrument set is provided by the projection of the derivative of the error term respect to the parameters onto the space spanned by the instruments, i.e.,

$$E[\frac{\partial \xi}{\partial \theta_1}|Z]. \tag{13}$$

Thus, if a regressor is in the instrument set, the optimal instrument is just the regressor itself since $E[\frac{\partial \xi}{\partial \theta_{1k}}|x_k] = x_k$. Assuming that unobserved product characteristics are uncorrelated with observed product characteristics that change only slowly over time appears natural. However, it may not be reasonable to impose a zero correlation between the unobserved product characteristic and observed product characteristics like the admission price which are potentially short term choice variables. These variables are likely correlated with unobserved product characteristics (unobservably high quality theaters are likely to charge high prices.) Thus, in some specifications I omit own price from the instrument set and must therefore find alternative instruments.

Berry, Levinsohn, and Pakes (1995) suggest using a set of functions of the available instruments designed to provide a first order approximation to the space spanned by the optimal instrument set. They note that the (series) approximation (Newey (1990)) suggested involves own product characteristics, a set of instruments obtained by summing over the characteristics of competing products, and a third set of instruments from summing over products sold by the same company. Although I found that instrumenting for price had little impact on the estimated price coefficient, I did experiment with a variety of instrumental variable approaches. The results reported in the next section construct a single instrument for price by performing an auxiliary regression of the theater's admission price on the exogenous observed product characteristics, and the number of other films of each type playing in other theaters.

Instruments for the non-linear parameters were constructed by developing theater specific demographic and distance metrics. For example, the distance coefficient is identified by using the restriction that the unobserved theater characteristic is uncorrelated with the number of people who live within five

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there exist an optimal set of instruments, that which minimizes the asymptotic variance of our estimator (Chamberlain (1987)).

and ten mile radii of the theater.

5 Estimation Results

To aid interpretation of the estimation results for the full model, and to demonstrate that there are clear geographic and demographic patterns in market shares revealed by the data, Table (12) reports parameter estimates for the product level logit model with an unobserved product characteristic. This model, proposed by Berry (1994), is estimated using a simple two stage least squares regression proceedure, and provides a well understood benchmark to compare the results from the full model against. In all specifications, geographic and demographic characteristics are included in a reduced form manner by constructing additional "theater" characteristics describing the distribution of the population around the theaters. Geographic characteristics include the number of people living within a one, five, and ten mile radius of the theater. Similarly, theater level demographic characteristics may be constructed by defining variables such as the fraction of the population aged below twenty-five who live within a one, five, and ten miles of the theater. Constructing geographic and demographic theater characteristics in this fashion enables the model to explain observed variation in market shares across theaters resulting from, say, a large number of people living close to a theater. However, in contrast to the substitution patterns identified using the full model, these specifications continue to impose the unreasonable IIA restrictions on the possible substitution patterns between theaters.

Four specifications of the linear model are estimated. Column (1) reports parameter estimates using data from all 621 theaters for which sales data were observed, assuming that all observed product characteristics are uncorrelated with the unobserved product characteristic. Column (2) uses the same data, but instruments adult admission price by assuming that price is, and the unobserved product characteristic is not, correlated with the number of other theaters playing each other film being shown, à la Berry, Levinsohn, and Pakes (1995).[36] Columns (3) and (4) report estimates of each model using

[36] Specifically, a single instrument for price is constructed by performing a first stage regression of the adult admission price on the exogenous theater characteristics and the number of rival theaters playing each other film in the market. By constructing a single instrument for price, no over-identifying restrictions are imposed during estimation of

only data from theaters which charged an adult admission price of more than \$3. (I.e., excluding all second run theaters.)

The estimated price coefficient does not change substantially between the regressions reported in columns (1) and (2). There is no evidence that endogeneity bias in the price coefficient estimates will be introduced by assuming that the prices are uncorrelated with ξ. However, columns (3) and (4) demonstrate that the price coefficient in these regressions is sensitive to the exclusion of the 193 observations from second run theaters for which sales data are observed. Since second run theaters are clearly substitutes for movies shown on first run screens, I shall focus on the results from the full sample regressions. However, I emphasize this issue because the price coefficient is used to translate units of utility into units of dollars. Consequently, uncertainty about the price coefficient translates immediately into uncertainty about absolute dollar figures reported below in some of the policy experiments. Absolute dollar figures will not be robust to the exclusion of the second run theaters. In contrast, relative statements such as which theater locations improve consumer welfare will be robust to the exclusion of the second run theaters.[37]

In each of the specifications, all other estimated mean utility parameters have intuitive signs and are robust to the inclusion or exclusion of observations from second run theaters. Digital and THX screens[38] provide positive marginal utility to consumers. Comparing the coefficients on Price, and THX or Digital from the full sample results in columns (1) or (2), suggest that consumers receive approximately the same increase in utility from either a \$1 decrease in the price of admission, or moving the film onto a digital or a THX screen.

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the model. I prefer this approach because of the large small sample biases that can easily result from imposing multiple moment restrictions, even when those restrictions are correct assymptotically.

[37]In Davis (1999a) 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, I estimate the price coefficient in the product level logit model to be -0.1.

[38]Week is the number of weeks that the film had played at that particular theater while THX and digital are dummy variables describing whether the film played in an THX auditorium and/or with digital sound. THX is not another type of sound system, but rather a certification of high auditorium quality. Individual auditoria are certified rather than the theater as a whole. Thus THX and digital are not mutually exclusive.

The point estimates suggest that the greater the number of weeks a film has played on a screen, the lower the indirect utility received from attending. However, this effect appears statistically insignificant. This is not particularly surprising because these results are derived using only of one week of data and daily time dummies are included in the regression.

The impact of geographic and demographic variation in the populations served by these movie theaters is also clear from Table 12. For example, the more people which live within a five mile radius of the theater has a statistically significant large positive impact on attendance. An additional $100,000$ people in the five mile zone increases sales in a fashion approximately equivalent to installing digital sound into a theater.[39] The parameter estimates also suggest that an increase in the proportion of the population under aged 25 living within five miles of the theater from say 5% to 10% increases sales in a fashion approximately equivalent to installing digital sound, the fraction of the population over 55 living within one mile of the theater increases attendance, the fraction of the population which are african american or other races decreases attendance,[40] and the fraction of the population earning more than $50,000 per year increases attendance.

Table (13) reports parameter estimates for several alternative specifications of the full model. In each case, the mean utility parameters have intuitive signs and remain at similar values in the linear and full models. In the logit model, all variation in demand for the same film between theaters is explained by theater characteristics. The full model, in contrast, enables variation to be explained by the distribution of consumers and their characteristics within a market. Moreover, predicted substitution patterns depend on the distribution of consumers. First, the mean effect of travel distance, enters all specifications 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 $63 - distance$ cents in most regions of the country and $105 - distance$ cents in the west of the United States. Reducing the distance a consumer is required to travel by one mile increases the amount

[39] Adding digital sound is probably best interpreted as a proxy for a general improvement in auditorium quality.

[40] These latter effects may not be picking up preferences, but rather market structure features such as the fact that the non-white population is likely to live in higher crime regions of cities which are therefore less attractive to visit. Curiously, this point is always made in seminars given in cities like Washington D.C. and New York.

they would be willing to pay for admission by about 63/105 cents initially, but the marginal cost of travel declines as the distance increases.[41]

In the full model, each consumer has a distinct taste for distance, prices, and sound. Consumer tastes are assumed to vary in a systematic way with their demographic characteristics and also potentially in a non-systematic way within each demographic group. The non-systematic component of tastes is characterized by a normal distribution as specified in equation (2).

The important interaction term appears to be between age and the outside good. These parameters are econometrically identified by imposing moment conditions restricting the average predicted age distribution of consumers to be equal to the observed distribution and show that older consumers have significantly better outside options than younger consumers (dramatic arts, opera, going to Paris for the weekend...) and/or a higher opportunity cost of time. Once geographic and demographic variables were allowed for no further role for consumer taste heterogeneity could be identified.[42]

6 Distance and Cross Price Elasticities

How much does geographic differentiation insulate retailers from price competition? Consumer borne travel costs imply that, ceteris paribus, stores close to one another provide good substitutes, those further apart worse. For example, consider a theater which charges \$7.50 for admission. An individual should not rationally travel very far to save 25 cents of the admission price.[43] Regulatory authorities evidently believe that the potential to exploit local market power exists, as they frequently require that individual retail stores are sold off to avoid the problem arising.[44]

[41] $\frac{\gamma_{distance}}{\gamma_{price}} = \frac{-0.20(-0.12)-0.002*distance}{-0.19} = 0.63(1.05) - 0.01 * distance$

[42] An earlier version of this paper reported estimated parameter values for the interactions between consumer and product characteristics. These results are obtained using a large number of BLP style over-identifying restrictions which appear to significantly bias some of the parameter estimates.

[43] 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.]

[44] A 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. The recent merger between Sony and Cineplex

	$No - geog$		$full\ model$	
Variable	Parameter (x1e5)	(t)	Parameter (x1e5)	(t)
$Constant$	765	(17.6)	1215	(17.6)
$Distance$	-0.27	(-2.65)	-3.15	(-19.3)
$Distance^2$	-0.0001	(0.14)	0.02	(11.0)
$Distance * samefilm$	-0.26	(-5.38)	-0.18	(-2.42)
$Distance^2 * samefilm$	0.003	(4.02)	0.002	(2.01)
$Same\ film$	13.29	(21.32)	12.49	(12.68)
$Same\ chain$	2.89	(2.29)	4.21	(2.12)

Table 3: The dependent variable is the estimated cross price elasticity of demand, $\frac{\partial \log s_h}{\partial \log p_g}$ for each pair of theaters in the sample from model (3) in 13. 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.

The full demand model provides estimates of the cross price elasticity of demand for each pair of theaters in the sample. Table 3 reports a descriptive regression which relates the estimated cross price elasticity between two theaters to the distance between them, the number of films playing at both theaters, and whether the theaters are owned by the same theater chain. Though the analogous regression results for the logit model are shown, the logit cross price elasticities are deterministic functions of market shares and prices.[45]

The results are extremely intuitive. First, cross-price elasticities decline significantly, but at a decreasing rate as the distance between two theaters

Odeon provides another example where divestment of specific theaters were required: 14 theaters on Manhattan and 11 theaters in Chicago. Indeed, the specifics of location make regular appearances at FTC 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.

[45]The formulae for own- and cross-price elasticities between theaters are aggregated across products sold at the theater as follows:

$$\frac{\partial log s_h}{\partial log p_g} = \frac{p_g}{\sum_{f \in \mathcal{F}_h} s_{fh}} \sum_{f \in \mathcal{F}_h} \frac{\partial s_{fh}}{\partial p_g} \tag{14}$$

increases. Theaters which show a large number of the same films have a much higher cross-price elasticity of demand, as do theaters owned by the same circuit. The negative interaction between Same film and Distance shows that the increase in cross price elasticity from playing the same films decreases with the distance between theaters. Broadly, the patterns in both the logit and full models are very similar. However, the coefficient on the constant term indicates that the level of the cross price elasticities in the full model is much higher for two theaters close to one another. Similarly, given that higher base, the full model indicates that the estimated cross price elasticity declines faster in distance than the results from the logit model suggest.

The estimated relationship between cross-price elasticities and distance is useful in a variety of economic applications, most prominently for merger analysis in geographically differentiated markets.[46] Combining the estimated demand system with a pricing rule and information on marginal costs determines the appropriate market definition, the geographic area in which a hypothetical profit-maximizing monopolist would impose at least a 5% increase in price. The appropriate market definition is of crucial importance in merger cases; indeed in differentiated product markets, "the main battlefield in litigated merger cases is market definition" (Shapiro (1995)).

7 Welfare Consequences of Relocation

In this section, I use the demand model to perform a first set of policy experiments. Selecting a single theater at random, I consider how theater revenue, industry revenue, and consumer welfare change as the theater is moved from its present location to alternate feasible locations. The aim

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where $\mathcal{F}_h$ denotes the set of films showing at theater h, and

$$\frac{\partial s_{fh}}{\partial p_g} = -\int \alpha(\nu) s_{fh}(\nu, D, L)(I(g=h) - \sum_{l \in \mathcal{F}_g} s_{lg}(\nu, D, L)) dP^*(\nu, D, L). \tag{15}$$

where $I(g=h)$ denotes an indicator function which takes on the value 1 if $(\cdot)$ is true. In the logit model $P^*(\nu, D, L) = 1$ and $\alpha(\nu) = \alpha$, constant across individuals.

[46] Testing for local market power also contributes to the debate over Galbraith's hypothesis of countervailing market power, which relies on the existence of local market power in the downstream retail market. I note this example because the Exhibition market in Las Vegas was the scene of a recent, failed, attempt to invoke countervailing market power as a violation of the Sherman act. See US v. Syfu (1990) (F. 2d 659 (9th Cir.)).

is to compare the marginal incentives facing a theater owner, the industry, and the social planner when making store location decisions and to provide a comparative static description of the impact of moving away from the exisiting distribution of theater locations.

The differences between a retail store owner's private incentives, and social objectives has provided considerable debate since the seminal work of Hotelling (1929)[47] showed that consumer paid travel costs and the business stealing effect imply that private and social incentives do not generally coincide. Consequently the market allocation process may result in inefficient resource allocation.[48]

Figure 1 describes the industry revenue and consumer welfare which results from reallocating a single theater, the Northwest 14 in San Antonio Texas, to other feasible locations holding all prices, films and theater characteristics at their existing values. The set of feasible locations is assumed to be the central points of each census tract in the market and the existing theater locations. The figures demonstrate that industry revenue and consumer welfare are maximized with the Northwest 14 moved toward the central area of the city. At present, all except one of the theaters are located on the outskirts of the city and the welfare and revenue improvements generally result when the theater is (hypothetically) moved toward the center of the market area. The gains in consumer welfare from reallocating a theater optimally remain reasonably modest, the optimal relocation providing a $340 improvement in aggregate consumer welfare for this Saturday evening, against an industry revenue of approximately $158,000. Using reasonable assumptions

[47] Hotelling (1929) showed that if the set of feasible location choices are the $[0, 1]$ interval, consumers are located uniformly over the interval and pay a constant disutility cost per unit of travel then firms' equilibrium location strategies involve minimally differentiating themselves from their rivals while the social objective involves equi-spacing retail stores across the market.

[48] Naturally, the existence of theater revenue increasing relocations does not mean that such relocations would in fact be profitable. Land, and perhaps operating, costs are certainly higher in some central business districts. In addition such a move is away from the status quo and might also result strategic repositioning of rival theaters. While such caveats are important for interpretation of the results, the aim of this section is to provide a comparative static analysis as we move away from that status quo.

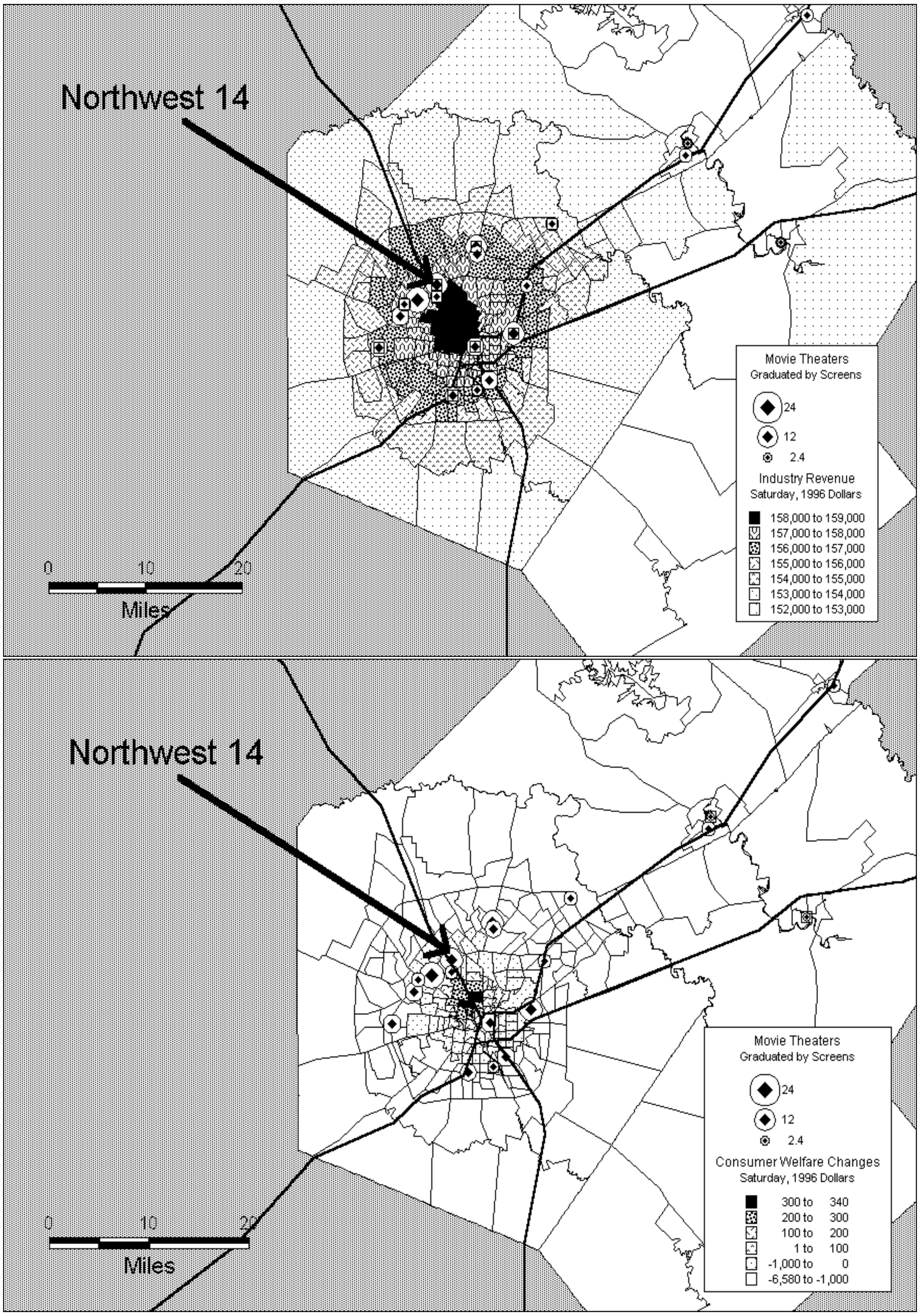

Figure 1: The figure shows how consumer welfare and industry revenue vary as a single theater, the Northwest 14 in San Antonio Texas, is reallocated to each census tract in the market area. Figures represent Industry revenue, and population times the average consumer equivalent variation for the change from a single day, Saturday 22nd June 1996. Note that theater owners would receive only a fraction of the change in revenue. The rest would be returned to the film distributors.

this aggregates to an annual gain of approximately $70,720.[49] These potential welfare gains look small, but do leave open the possibility that elected officials who provide modest financial inducements to encourage location in under-served areas of town may provide net welfare benefits to their average constituent.[50]

8 Entry and Scale

In this section, I examine the asymmetric impact of a new theater's entry on existing theaters and then 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. The asymmetric fashion in which a new entrant cannibalizes business from existing stores may be observed directly from the demand system, while determining the optimal theater scale requires both a model of supply and demand. Therefore, in this section, I develop a model of supply by obtaining data on theater costs and estimating an hedonic cost function for a theater. I subsequently use it together with the demand system to examine these issues under the assumption that theater owners maximize profits while the social objective is to maximize welfare, defined as consumer surplus plus industry profits.

Mankiw and Whinston (1986) showed that business stealing generally results in socially excessive entry in homogeneous product industries. When products are differentiated, the incentive to introduce excessive numbers of products may be tempered, or indeed overwhelmed, by the welfare gains resulting from increased product diversity. Surprisingly, 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 would result from welfare maximization. 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

[49] Saturday evenings generate approximately one quarter of weekly theater revenues. Hence 340x4x52 = $74,720$ provides a rough estimate of the implied annual net gain to consumers.

[50] Note however that it is extremely unlikely that there will ever be a pareto improving theater relocation; there will always be consumers whose travel costs are increased when implementing such a policy.

rich demand system presented here, consumers are heterogeneous in several dimensions and therefore the returns to diversity can potentially be considerably larger. In addition, there are revenue sharing arrangements in the movie industry which could substantially affect the magnitude of the business stealing effect.

8.1 Estimating Theater Costs

Recently, the New Empirical IO literature (Bresnahan (1989)) has advocated inferring a firm's marginal cost from an equilibrium pricing equation (see for example Rosse (1970), Bresnahan (1987), Berry, Levinsohn, and Pakes (1995), Graddy (1995), or Nevo (1998)). This approach has the advantage of not requiring data on firm costs that is often difficult to obtain. Unfortunately, the elicited cost information relies heavily upon the equilibrium assumption, an assumption which is not consistent with the film industry's practice of charging a single price for admission to a theater, irrespective of the quality of film. A second approach which also avoids the need to rely upon cost data, taken in recent studies of entry, is to infer the distribution of firm's costs from the equilibrium entry conditions; that active firms make non-negative profits while potential entrants make non-positive profits (See Bresnahan and Reiss (1990), ;Berry (1992), and Davis (1999b), or Toivanen and Waterson (2000) for a survey). In these studies, the authors explicitly treat firms as perfect substitutes after the entry decision is made so that post-entry profits depend only on the number of firms.[51] A geographically differentiated market requires that firm's are allowed to be asymmetric post entry; theaters are in different locations.

Rather than attempt to use one of these ingenious approaches in an inappropriate institutional environment, I choose to estimate theater costs from the available cost data directly. Estimates of construction costs are, 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.[52] While many permits were missing, I did manage to obtain cost data for 140 theaters.

[51] See Berry and Waldfogel (1996) for an estimate of the welfare loss from excess entry under the ex-post symmetry assumption.

[52] 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.

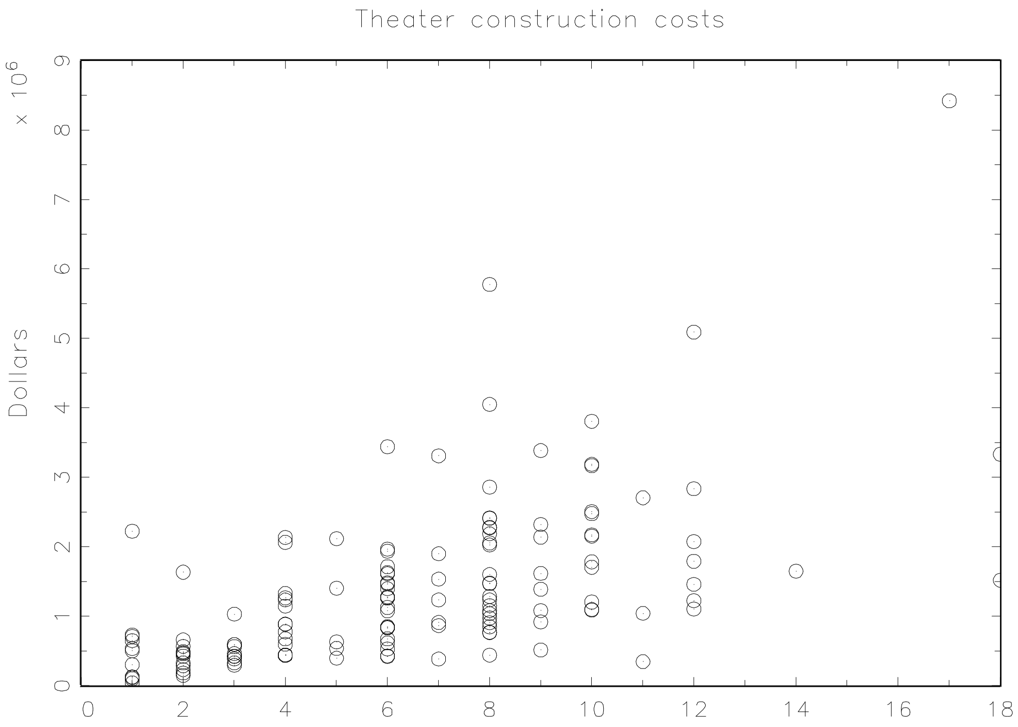

Figure 2: Theater construction costs as a function of theater scale.

The most expensive theater in the sample cost \$8.25 million to build, while the cheapest theater cost only \$42,000.[53] Figure 2 presents the construction cost data as a function of theater scale. Average construction costs increase as the scale increases as expected, moreover the spread of the distribution of increases dramatically with scale.

Table 8.1 below reports hedonic regression results using the construction cost data. The estimated model of costs is

$$C_i = \alpha_0 + \alpha_1 s_i^L + \alpha_2 (s_i^L)^2 + \alpha_3 s_i^H + \nu_i \tag{16}$$

Where possible, I verified and/or augmented the permit information using building valuations from local tax authorities.

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

	(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 4: Estimated construction cost functions. Reported t statistics are calculated using heteroskedasticity consistent standard errors, White (1982).

where, s^L and s^H are the number of low (stereo) and high (digital) quality screens at the theater. The unobserved component of costs is assumed to have a variance which increases in the observed determinants of costs:

$$E[\nu_i] = 0 \text{ and, } \quad Var[\nu_i] = \sigma * E[C_i]^2.$$

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 $(1/E[\hat{C}_i]^2)$ for the second stage.

The more general specification, reported in column 1, models costs as quadratic in the number of stereo screens and increasing in a the number of digital screens at the theater. 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 16. I also considered regional effects and a quadratic term in the number of digital screens. Insignificant parameter values were obtained in each case.

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,[54] roughly \$ 6,000 for DTS (Digital theater sound) and \$ 9,000 for SDDS (Sony Dynamic Digital Sound). Hence I interpret α_3 as the costs of a high quality auditorium, rather than merely converting an auditorium to digital sound.

8.2 Theater Scale

The profit maximizing firm chooses to build the number of mono and digital screens that maximize profits

$$\max_{(s^L,s^H)} \psi E[R_h(s^L, s^H)|s^L, s^H] - C(s^L, s^H)$$

where $E[R(s^L, s^H)|s^L, s^H]$ represents the expected theater revenue and $C(s^L, s^H)$ is theater construction costs and ψ is a parameter which makes the revenue predictions of the model and the cost data comparable. Specifically, ψ adjusts the revenue prediction from the demand model for concessions revenue, film rental payments, and inflates the weekly revenue figure determined from the demand system to the expected lifetime revenue of the theater. Similarly, the parameter is also assumed to account for other costs such as land and operating cost increases as the theater's scale changes.[55]

Expectations are taken with respect to the distribution of film qualities. In order to avoid modeling the film allocation process explicitly, I try a variety of reduced form approaches to modeling the allocation of films to the new theater while assuming that the film qualities received by rivals remains unchanged. The first is to assume that the theater receives films of the lowest quality. The second set of results assume that the theater obtains films of the mean quality. Finally, a set of results are reported assuming that the theater obtains the highest quality films. In contrast to the first two sets of results the latter is calculated without replacement so that the quality of film an additional screen receives declines in the number of screens. Since the latter is the typical situation faced by large new multi-plex theaters, I focus on these results while providing the others to illustrate which results are sensitive to this assumption.

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

[55] This calculation clearly has the flavor of a back of the envelop calculation. Nonetheless, the qualitative results described below are unlikely to be changed by such complicating factors.

8.3 Theater Scale: Policy Experiments

I consider the arrival of a sixteen screen multiplex theater built in the San Antonio, Texas, market during late 1996.

Figure 8.3 shows the business stealing and market expansion effects resulting when a new theater is built under three different assumptions about the quality of films the new theater receives, conditioning upon the decisions of previous entrants and the location and pricing decisions of the new theater. As expected, the level of the market expansion and business stealing effects depend heavily on the set of products for sale. The effects appear virtually linear in theater scale when films are drawn *with replacement* from the distribution of film qualities. Adding new products at a constant quality level does not appear to result in dramatic reductions in marginal revenue. In contrast, when the distribution of film qualities are sampled without replacement, so that building an extra screen involves showing a lower mean utility film, a distinct, concave, revenue function emerges (c.f. BS3 and ME3). Which ever film allocation procedure is assumed, the Business stealing effect corresponds to approximately 4 percent of new theater revenues.

In comparison to previous studies, Berry and Waldfogel (1996), the business stealing effect appears modest. In contrast to earlier work however, business stealing does not occur equally across competitors. Figure 8.3 demonstrates the magnitude of the asymmetric business stealing effects. These calculations correspond to film allocation mechanism 3; that the new theater obtains films in decreasing order of available quality. The top panel illustrates how business stealing increases with the scale of new entry. Moreover, for any given scale of the new entrant, business is stolen from rivals asymmetrically. The absolute magnitude of stolen revenues differs dramatically across competitors according to the rival's scale and other theater characteristics, including location. For example, the top two curves correspond to business stolen from the two fourteen screen theaters in San Antonio, TX which are closest to the new theater's location. In order to isolate the effect of rival's distance from other theater characteristics, the bottom panel in Figure 8.3 reports business stealing as a percentage of initial revenues when the new entrant builds 16 screens, as actually occurred. Notice that incumbents which are only four miles away from the new entrant see a much larger fall in business than rivals who are further away.

Welfare effects from introducing the 16 screen Fiesta cinema appear quite modest on a per capita basis, at most 0.4 cents per person per day. However,

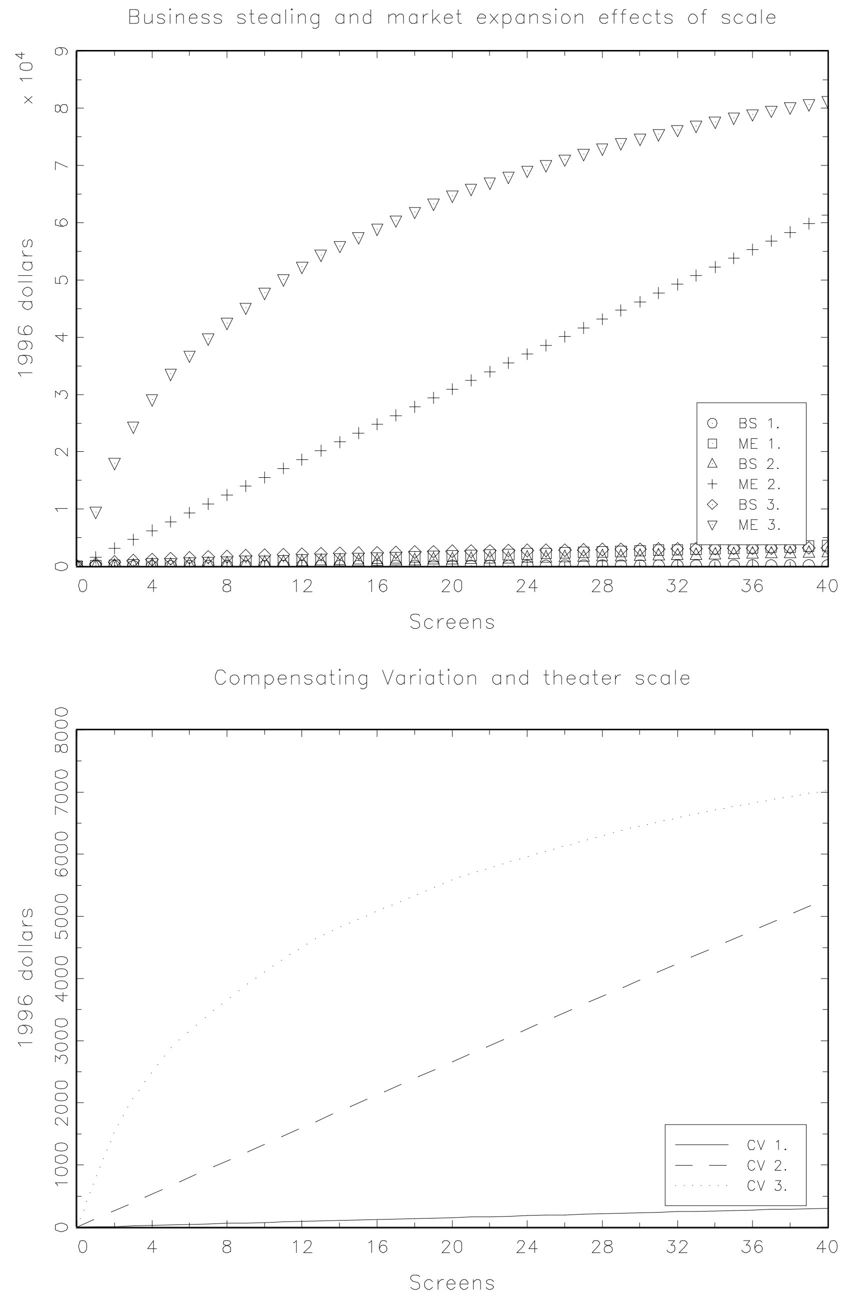

Figure 3: BS denotes Business stealing while ME represents the Market Expansion effect and CV is the compensating variation arising from building new screens. All figures are in 1996 dollars. Revenue figures in the top panel represent the business stealing effect and market expansion on a single Saturday evening. The results for three film quality distributions are reported here. BS1 and ME1 are calculated by assuming the theater obtains films of the lowest observed quality level. BS2 and ME2 are calculated by assuming that the theater obtains films of the mean quality level, while BS3 and ME3 are calculated assuming that the theater obtains the highest quality films available. The latter theater qualities are drawn from the observed distribution of delta's *without* replacement. Consequently, the second screen built must show a lower quality film. The third film allocation mechanism represents an upper bound on theater revenues, but also probably constitutes the most reasonable assumption about this new entrant since the theater's entry strategy was clearly to enter at the top of the quality distribution. Evidence of this entry strategy includes the fact that all sixteen of the theater's auditoria were equipped with digital sound systems.

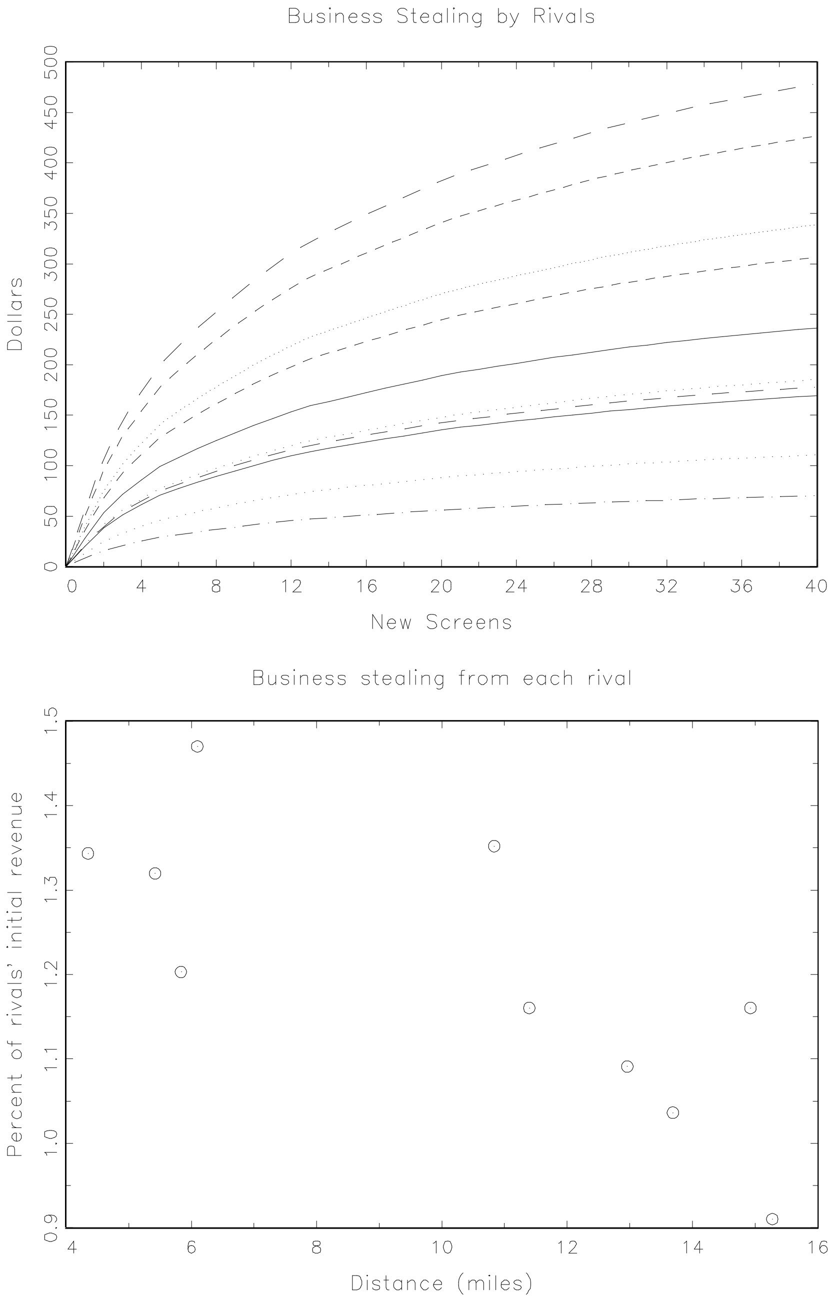

Figure 4: The top panel presents the absolute magnitude of the daily business stolen from each rival as the scale of the new entrant increases. The asymmetry of the business stealing effect is clear: Two close, fourteen screen, theaters account for a significant fraction of the total business stolen from incumbents. The bottom panel fixes the scale of the new entrant, to the actual 16 screens, showing the predicted percentage of business stolen declines steadily with the distance from the new entry site.

in aggregate, these modest welfare effects are quite significant - amounting to approximately \$4,950 per day or approximately \$1 million per year.[56]

Figure 8.3 presents the optimal scale calculations as a function of the model's parameter ψ. For each value of ψ, the private (theater profit maximizing), the collusive (industry profit maximizing) and welfare maximizing scale choices are shown.

As expected, the collusive scale choice is everywhere smaller than the privately optimal scale because the industry internalizes the business stealing effect. In particular, the model predicts that a collusive industry would build a 13 screen theater when the privately optimal decision is to build 16 screens. The welfare gains from, and effects of, new screen introduction are predicted to be sufficient to induce the social planner to build theaters with as many as 20 screens.[57] The reasons are twofold. First, the magnitude of the business stealing effect is found to be small relative to the consumer surplus gains. Second, the 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 uncaptured consumer surplus can be biased toward the dominance of the uncaptured 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.[58]

[56]As before, this figure is calculated under the assumption that the weekly consumer surplus is four times the Saturday consumer surplus figure. Thus annual consumer surplus = 4x52x4950.

[57]These welfare calculations are subject to the critique in Petrin (1998) because, in contrast to the location experiments reported above, they introduce a new product and hence each individual obtains a new draw on the Type I extreme value error. The "logit" error term provides considerable analytic convenience, but has no structural interpretation. 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 psi can result in discrete changes in the optimal number of screens.

[58]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 dramatic trends recently observed in the industry. Specifically, the model predicts that increased vertical integration will be accompanied by more and

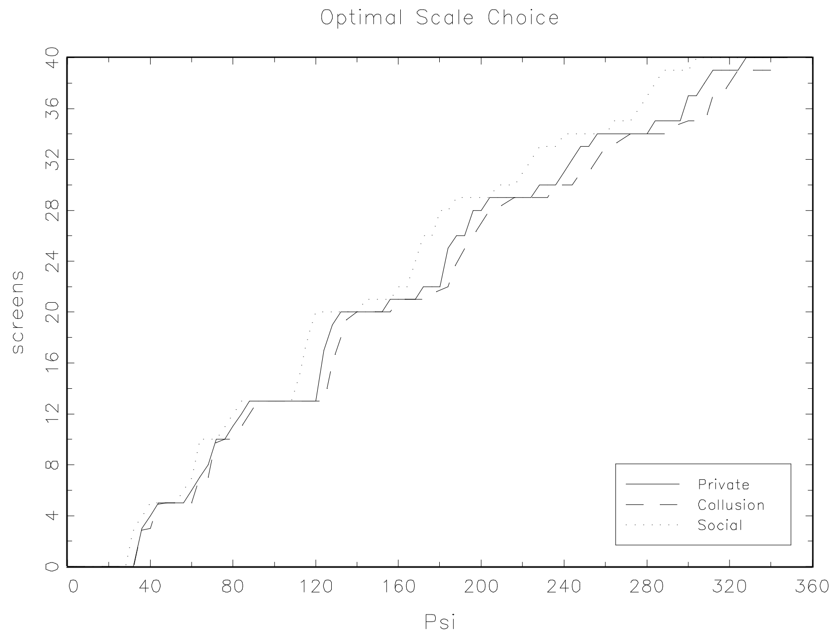

Figure 5: The figure presents private, collusive and socially optimal scale computations as a function of the parameter ψ, assuming that the theater receives films in order of quality - corresponding to film allocation method 3 above.

9 Conclusions

In contrast to a competitive market, where a large number of buyers and sellers meet freely, retail markets operate in a complex system of scattered buyers and sellers (Gabszewicz and Thisse (1986)). These complex markets have been extensively studied using stylized theoretical models such as Hotelling's (1929) linear city with a uniform distribution of consumers and Salop's (1979) circular city. For example, many authors have considered the question of whether retail markets result in stores which locate "too close" or "too far" from one another, relative to their socially desirable locations. Through a Herculean effort, these literatures have refined our understanding of the often counterbalancing economic forces at play.

Unfortunately, few tangible policy or management conclusions have emerged from all this activity. Although we have shown in principle that stores may locate "too far" apart or "too close" together in a linear city, it has proven difficult to draw practical implications from such conclusions. The reason is that whether two stores are actually too far apart or too close together has proven to be heavily dependent on the distribution of consumers, the geographic structure of the market, and the structure of consumer's preferences. In fact, as Spence (1976) notes, all welfare calculations of the form used to compare social and privately optimal behavior are performed only relative to the distribution of purchasers. Thus, abstracting to analytically tractable models by making invalid assumptions regarding the distribution of consumers necessarily introduces extreme difficulties for the applicability of the results in practical matters such as policy analysis or as management tools.

The aim of this paper is to develop a framework suitable for performing policy analysis in retail markets. To do so, I show how the observed distribution of consumers, and implicitly many physical aspects of actual market structure, may be incorporated into an estimable model of firm and consumer behavior in retail markets. I use the estimated model to address two questions. First, to what degree does geographic differentiation provide retail stores with market power? Second, I consider how differences between private and social incentives influence store location and scale decisions.

In order to provide answers to these questions I estimate a product-level demand and cost system for movie theaters, a small but culturally signifi-

larger movie theaters.

cant component of the retail sector. Census tract data provide a rich non-parametric description of the distribution of consumers within a market. Hence, variation in demand between store locations is explained partly by differences in product and store characteristics, but also by the distribution of consumers *within* the market. The distribution of consumers feeds directly into substitution patterns between stores. I estimate the model and perform three sets of policy experiments.

First I examine the relationship between cross-price elasticities and distance between competing theaters, a relationship that is of particular interest for merger-analysis in geographically differentiated markets. I find that theater demand is generally quite insensitive to rivals prices (cf. the opening quotation) but is more sensitive the closer the rival; cross price elasticities decrease significantly with distance.

Second I examine the counter-factual relocations of an existing theater away from the status quo. Assuming that the set of possible theater locations is the union of the set of existing locations and the mid points of each census tract, I find that private and social incentives for location do indeed differ, with uncaptured consumer welfare gains from moving theaters toward the center of town. However, the estimates of welfare gains suggest relatively modest differences between private and social returns.

Finally, I examine the scale choice of a new theater owner. I attempt to evaluate whether firms build theaters which are too large or small relative to the socially optimal scale. To do so, I combine a cost function for theaters using newly obtained cost data from individual theater building permits and examine the scale of entry of a new theater.

In any differentiated product market, differences between the socially and privately optimal number of products (here scale of a theater) depend on the balance of two opposing forces. On the one hand, business stealing tends to result in the over-provision of products. On the other hand, the firm's inability to capture all of the consumer surplus provided by a new product tends to result in the market under-providing new products. In contrast to much recent work on the optimal provision of products in differentiated product industries (see Mankiw and Whinston (1986), Anderson, de Palma, and Nesterov (1995),and Berry and Waldfogel (1996)), I find that the latter effect outweighs the former; products are *under*-provided by the market.

Although finding under-provision of products is surprising in light of the previous literature, the rich structure of geographic product differentiation and the structure of contracts between distributors and theater owners provide ready explanations. In particular, since products are horizontally differentiated in a very important way, the magnitude of the business stealing effect is estimated to be small while the benefits from new products are found to be large. In addition, the vertically disintegrated structure of most retailers in the exhibition market means that most theater owners capture only a fraction of revenues from an additional screen; the part which is not returned to the distributor. One consequence of this institutional arrangement, since business stealing is only a function of theater revenues, is that the contribution of business stealing to a theater's incentive to introduce a new product is smaller than it otherwise would be. Such revenue sharing contracts are also present in many other retail and media industries, for example video rental markets. The combination of these two effects ensure that an inability to capture even modest amounts of consumer surplus is sufficient to tip the balance toward the under-provision of differentiated products in the motion picture exhibition market.

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Market	*Concentration*		*Total*	*Price*			
	C_1	C_2	*Screens*	*mean*	*median*	*max*	*min*
Watertown, NY	94.	0	33	5.50	6.25	6.25	4
Evansville, IN	87.	13	58	5.46	5.63	6.50	4
Portland, OR	77.	8	344	4.81	5.50	8	1
San Antonio, TX	73.	15	290	4.67	5.50	6.50	1.50
Birmingham, AL	71.	29	154	4.90	6	6	1.50
Memphis, TN	66.	14	182	5.34	6	6	2
Madison, WI	66.	8	88	5.27	6	6.50	1.75
Mobile, AL	65.	14	146	4.87	5.75	6	1.50
Des Moines, IA	65.	16	131	4.95	5.25	6	2
Richmond, VA	65	25	163	5.24	6	10	0.99
Nashville, TN	62	21	306	5.03	6	6	0.99
Cincinatti, OH	60	15	218	4.71	5.75	7	0.99
St Louis, MO	57	20	368	4.43	5.75	6.25	1
Chattanooga,TN	56	40	89	4.42	6	6	1
Albuquerque,NM	54	15	160	5.09	6	6.50	1.50
Wichita, KS	52	17	96	4.34	5.25	6	1.25
Milwaukee, WI	48.	8	262	5.22	6	6.50	1.75
Eugene, OR	48	30	59	5.47	5.50	6	5
Tallahassee, FL	46	17	67	4.44	5.50	6	1.50
Austin, TX	46	16	179	5.06	5.63	6.50	1.50
Knoxville, TN	43	40	110	4.87	5.75	6	1.50
Louisville, KY	37	25	122	4.52	5.50	7	1
Littlerock, AR	34	23	99	4.80	5.50	5.75	1.50
Tulsa ,OK	33	26	97	4.63	5.25	6.25	1.25
Cleveland, OH	33	18	296	5.49	6.25	6.75	1.50
Baltimore, MD	33	20	252	5.81	6.50	7.50	1.50
Denver, CO	31	23	364	5.50	6.25	6.75	1.50
Columbia, MO	31	21	101	5.48	6	6	1.50
Tampa, FL	30	24	351	4.34	5.50	6.25	1
Houston, TX	26	22	506	5.00	5.75	7	1
Saltlake, UT	25	21	266	4.58	5.25	6	1.50
Indianapolis, IN	25	20	227	4.99	6	7	1.50
Jacksonville, FL	23	19	165	4.86	5.75	6	2
Oklahoma, OK	23	16	171	4.72	5.75	6.25	1.50
Charleston, SC	22	20	84	5.59	6	6.25	2
Charlotte, NC	21	19	240	5.06	5.75	6	1
means	48	19	190	4.99	5.78	6.48	1.65

Table 5: Concentration and prices. C_n denotes the n firm chain concentration ratio, calculated by screen count. Independents are included in the total screen count, but excluded from the calculation of concentration ratio's. Hence C_2 may equal zero, even though $C_1 < 100\%$. Market concentration by revenue would be higher, but revenues are not available for all screens.

Number of Screens	Number of Theaters	Percentage of screens	Percentage of Theaters
1	27	1	4
2	53	3	9
3	51	4	8
4	69	7	11
5	41	5	7
6	118	18	19
7	27	5	4
8	92	19	15
9	22	5	4
10	60	15	10
11	6	2	1
12	23	7	4
13	2	1	0
14	13	5	2
16	2	1	0
17	1	0	0
18	2	1	0
20	1	1	0
22	1	1	0
24	1	1	0

Table 6: The distribution of theaters by size.

Screen Count	mean	st. dev	median	max	min
raw	81	9.6	81	100	53
price weighted	88	7.6	90	100	68

Table 7: Summary statistics describing the percentage' of screens (first and second run) covered by EDI's data across markets in this sample. Sample 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.(iii) Understate fraction of revenue covered since the distribution of sales is highly skewed.

Variable	mean	median	max	min	stdc
Technological					
Running time	103.738	101.000	169.000	73.000	17.596
Aspect Ratio	1.878	1.780	2.350	1.660	0.282
Log(age)	4.252	4.317	6.234	1.609	0.959
Dolby digital	0.323	0.000	1.000	0.000	0.471
DTS	0.262	0.000	1.000	0.000	0.443
SDDS	0.200	0.000	1.000	0.000	0.403
Rating					
Not Rated	0.031	0.000	1.000	0.000	0.174
R	0.462	0.000	1.000	0.000	0.502
PG 13	0.277	0.000	1.000	0.000	0.451
PG	0.169	0.000	1.000	0.000	0.378
G	0.062	0.000	1.000	0.000	0.242
Genre					
Re-release	0.046	0.000	1.000	0.000	0.211
Adventure	0.062	0.000	1.000	0.000	0.242
Animation	0.077	0.000	1.000	0.000	0.269
Action	0.200	0.000	1.000	0.000	0.403
Art	0.123	0.000	1.000	0.000	0.331
Comedy	0.323	0.000	1.000	0.000	0.471
Drama	0.277	0.000	1.000	0.000	0.451
Horror	0.031	0.000	1.000	0.000	0.174
Fantasy	0.077	0.000	1.000	0.000	0.269
Documentary	0.015	0.000	1.000	0.000	0.124
Sports	0.046	0.000	1.000	0.000	0.211
Foreign language	0.169	0.000	1.000	0.000	0.378

Table 8: Film characteristics. The table reports figures from 55 films. Genre variables were constructed using the *Internet Movie Database* classifications which are non exclusive. Ratings are determined by the Classification and Rating Authority (CARA). Age is the number of days since release in the United States. The dummy variables, Dolby digital, Digital Theater Sound (DTS) and Sony Dynamic Digital Sound (SDDS) represent the type of digital sound format used on each film, if any. In order to use a theater's digital sound equipment, films must have sound synchronization information and/or sound recorded on them in one digital format.

	income ($ 000's)								
age(years)	1-5	5-10	10-15	15-25	25-35	35-50	50-75	75-100	100-200
1-24	0.883	0.816	0.909	1.495	0.890	0.495	0.148	0.023	0.013
24-34	1.307	1.331	1.846	4.784	4.767	5.062	3.010	0.617	0.336
34-44	0.850	0.927	1.228	3.350	3.915	5.319	4.850	1.448	1.123
44-54	0.613	0.632	0.798	1.954	2.221	3.194	3.617	1.386	1.146
54-64	0.762	0.916	1.010	2.166	2.025	2.358	2.130	0.774	0.690
64-74	0.846	1.767	1.613	2.750	1.811	1.446	0.895	0.276	0.288
74-84	0.944	2.130	1.389	1.656	0.856	0.602	0.361	0.110	0.123

Table 9: Observed joint distribution of age and income (x100), averaged over all $9,506$ census tracts in 36 market areas.

Day	mean	st. dev	median	min	max	market	Film
Fri	19.31	30.94	7.49	0.07	272.33	17.4%	31.5%
Sat	24.31	36.95	10.60	0.18	325.88	20.5%	28.8%
Sun	17.97	27.02	7.65	0.05	223.33	22.4%	17.2%
Mon	7.96	12.80	3.34	0.03	111.41	20.7%	27.8%
Tues	7.86	12.15	3.26	0.10	101.57	20.0%	28.3%
Wed	8.04	12.16	3.75	0.06	95.24	21.4%	24.7%
Thurs	7.17	10.88	3.21	0.03	100.16	19.5%	21.9%

Table 10: Attendance per hundred thousand people at a single film within a single theater. The last two columns show the results from a two way analysis of variance; the percentage of variance in shares due to market and film dummies respectively (partial sum of squares divided by the total variation).

Day	mean	st. dev	median	min	max
Fri	1152.27	1709.38	531	4.00	25894.00
Sat	1442.28	1992.25	729	2.00	29812.00
Sun	1068.25	1554.88	520	3.00	23888.00
Mon	502.95	764.94	230	3.00	13385.00
Tues	462.66	666.38	226	3.00	10532.00
Wed	441.76	600.29	233	4.00	10889.00
Thur	420.15	587.00	228	2.00	12033.00

Table 11: Revenue for a single film at a theater by day. Units are US dollars. Number of observations = 20,008.

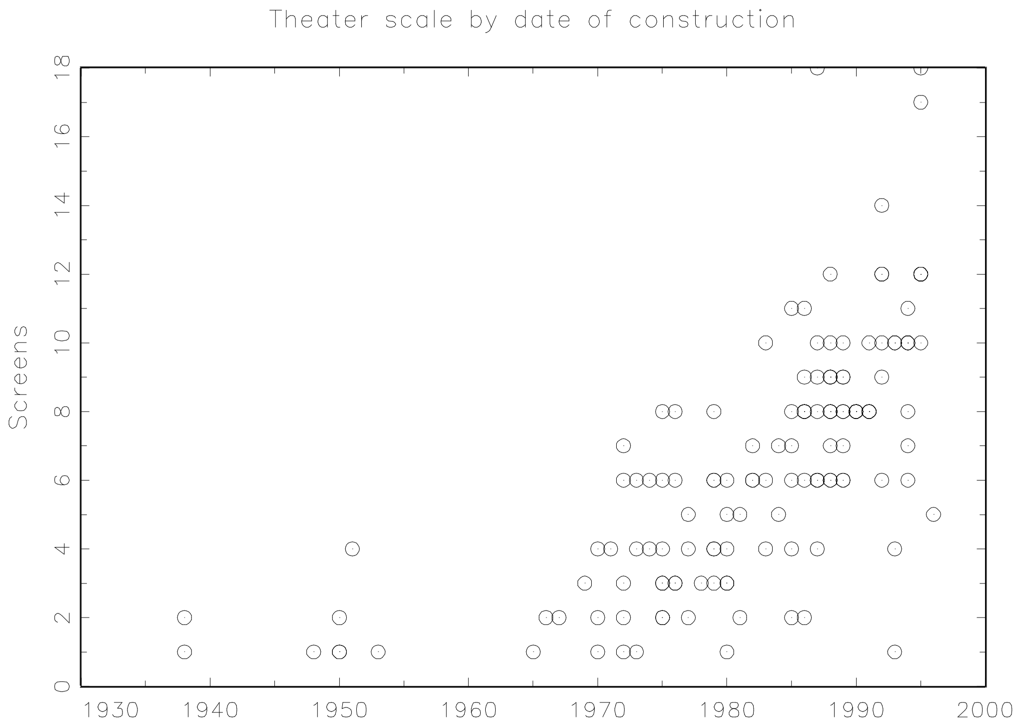

Figure 6: The figure shows the evolution of the distribution of the number of screens per theater in the subsample of theaters for which building permits were obtained.

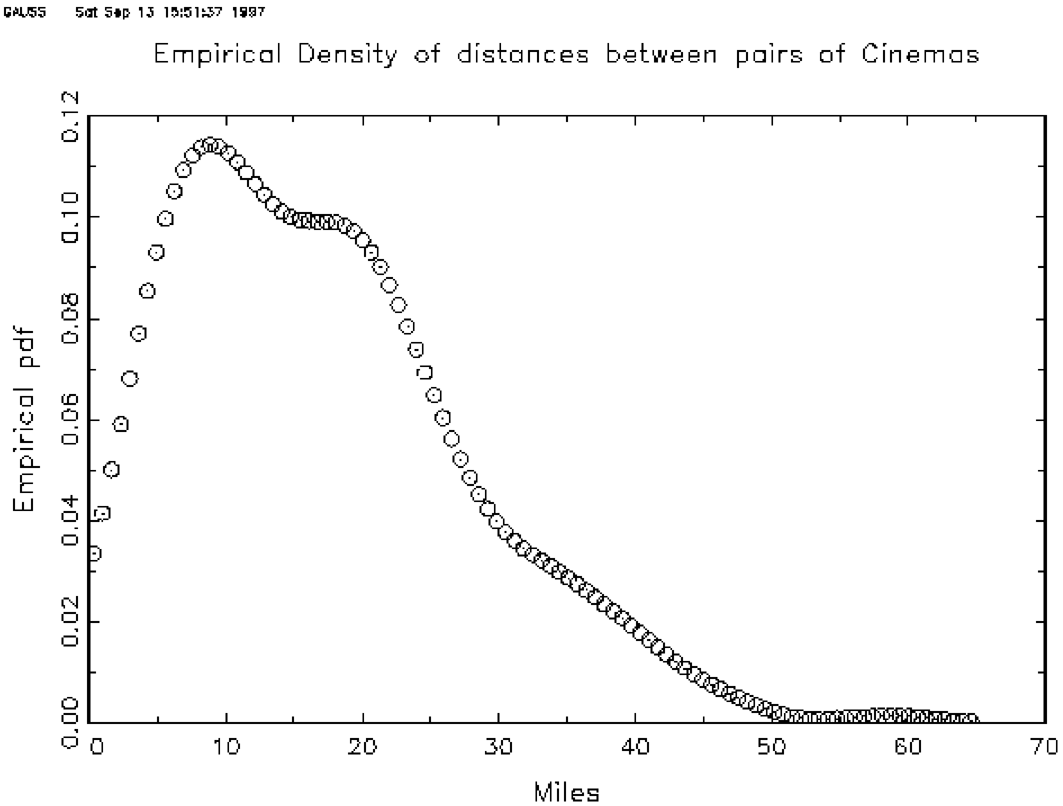

Figure 7: Non-parametric estimate of the Empirical density of distances between pairs of cinemas in the same market area. The maximum distance between two cinemas, in the *same* market area, is 146.5 miles. Estimate calculated using a normal kernel.

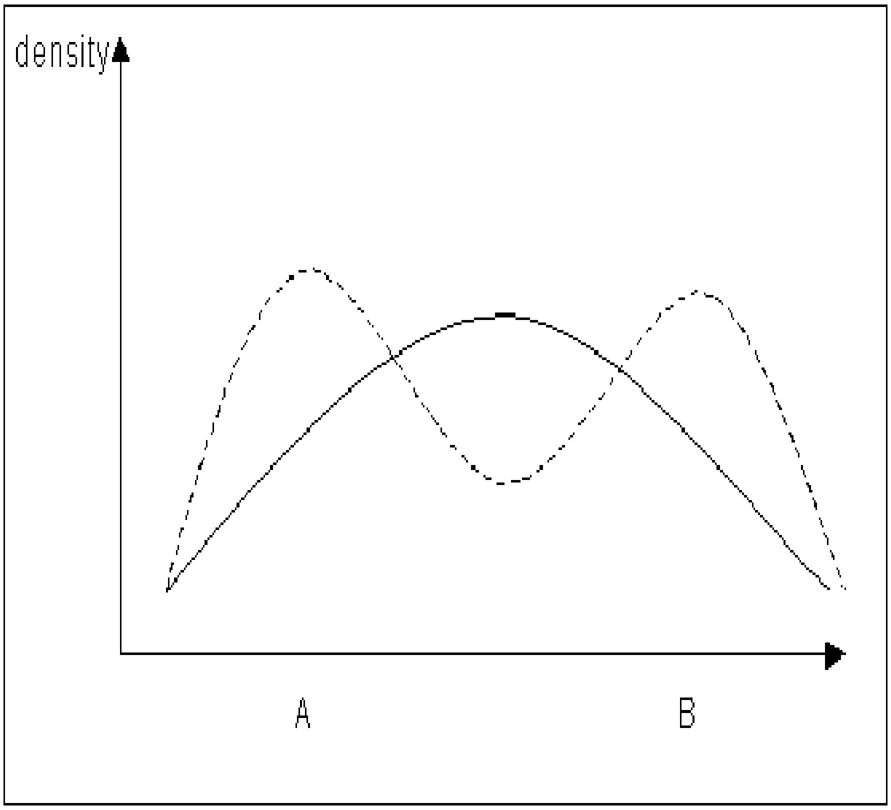

Figure 8: The figure shows the impact of the distribution of consumers locations on the cross elasticity of demand between two theaters located at A and B. The dotted graph shows a city wherein consumers are clustered in two areas, each served by a theater, while the solid line shows a single peaked density of consumers. The number of consumers who respond to a small price decrease at theater A will clearly depend on the density of consumers that are close to the boundary of indifference between the two theaters at the old price levels. Thus, the elasticity of demand with the solid density is likely to be larger than with the two peaked density.

Parm Name	(1)		(2)		(3)		(4)	
	Film and Theater Characteristics							
DIGITAL	0.25**	(0.03)	0.25**	(0.03)	0.22**	(0.03)	0.20**	(0.04)
Price	−0.22**	(0.02)	−0.23**	(0.08)	0.01	(0.03)	0.30	(0.27)
screens	0.05**	(0.01)	0.05**	(0.01)	0.05**	(0.01)	0.04**	(0.01)
thx	0.29**	(0.05)	0.29**	(0.05)	0.30**	(0.05)	0.30**	(0.05)
week	−0.02	(0.01)	−0.02	(0.02)	−0.01	(0.02)	−0.02	(0.02)
	Demographic and Geographic Theater Characteristics							
Population within x mile radius of theater (in millions)								
one mile	−1.51	(0.93)	−1.53	(0.94)	−2.32*	(1.05)	−1.62	(1.28)
five miles	2.16**	(0.41)	2.21**	(0.46)	2.08**	(0.41)	1.52*	(0.67)
ten miles	−0.11	(0.16)	−0.11	(0.16)	−0.27	(0.15)	−0.36*	(0.17)
Fraction of population within x miles of theater aged below 25								
one mile	0.96	(0.51)	0.96	(0.51)	0.91	(0.51)	0.74	(0.54)
five miles	4.48**	(1.27)	4.53**	(1.31)	4.27**	(1.26)	3.65*	(1.44)
ten miles	2.40	(1.72)	2.41	(1.72)	1.46	(1.70)	1.16	(1.74)
Fraction of population within x miles of theater aged above 55								
one mile	0.56*	(0.23)	0.56*	(0.23)	0.54*	(0.22)	0.54*	(0.22)
five mile	−0.06	(0.56)	−0.05	(0.57)	0.07	(0.56)	−0.20	(0.64)
ten mile	0.99	(0.67)	1.01	(0.67)	0.70	(0.67)	0.96	(0.73)
Fraction of population within x miles of theater earning less than \$ 15,000								
one mile	−0.04	(0.29)	−0.03	(0.29)	−0.07	(0.29)	−0.22	(0.32)
five miles	−1.20	(0.65)	−1.23	(0.66)	−1.01	(0.66)	−0.42	(0.87)
ten miles	0.15	(0.78)	0.18	(0.80)	0.29	(0.78)	0.24	(0.82)
Fraction of population within x miles of theater earning more than \$ 50,000								
one mile	0.15	(0.20)	0.17	(0.22)	0.29	(0.19)	0.11	(0.24)
five miles	1.69**	(0.41)	1.67**	(0.42)	1.55**	(0.41)	1.62**	(0.43)
ten miles	−0.58	(0.66)	−0.51	(0.72)	−0.71	(0.64)	−1.05	(0.72)
Fraction African American within x miles of theater								
one mile	−0.41*	(0.19)	−0.41*	(0.19)	−0.25	(0.19)	−0.13	(0.24)
five miles	0.46	(0.32)	0.45	(0.33)	0.29	(0.33)	0.13	(0.39)
ten miles	−0.71	(0.36)	−0.70	(0.36)	−0.56	(0.37)	−0.46	(0.39)
Fraction Not white or African American within x miles of theater								
one mile	−1.61**	(0.59)	−1.62**	(0.60)	−1.62**	(0.60)	−1.28	(0.70)
five miles	2.17	(1.50)	2.16	(1.50)	2.58	(1.48)	1.73	(1.69)
ten miles	−0.22	(1.75)	−0.16	(1.78)	−0.63	(1.74)	−0.06	(1.86)
gen. R^2	0.76		0.75		0.77		0.77	
Num.	3121.00		3121.00		2928.00		2928.00	

Table 12: Columns (1) to (4) report results for the product level logit incorporating demographic and population characteristics as theater characteristics. Adult admission price is treated as an exogenous variable in columns (1) and (3), while in columns (2) and (4) an instrument for price is constructed using other products characteristics in an auxilliary first stage regression. In columns (1) and (2), the regressions are reported for all 621 theaters. In columns (3) and (4), theaters with observed adult admission prices price below \$3 are excluded from regression. The results suggest that the estimated price coefficient is not sensitive to endogeneity, but is clearly identified in part by the observed variation in prices across first and second run theaters. **,* denote statistically different from zero at the 1% and 5% level of significance respectively. Standard errors are in parentheses and all specifications include market and film fixed effects.

Model Number	(1)		(2)		(3)	
Digital	0.34^{**}	(0.04)	0.31^{**}	(0.03)	0.31^{**}	(0.03)
Price	-0.20^{**}	(0.03)	-0.19^{**}	(0.02)	-0.19^{**}	(0.02)
Screens	0.05^{**}	(0.01)	0.05^{**}	(0.005)	0.04^{**}	(0.005)
THX	0.33^{**}	(0.06)	0.32^{**}	(0.05)	0.30^{**}	(0.05)
Week Number	-0.02	(0.03)	-0.03	(0.02)	-0.02	(0.01)
$\gamma_{distance}$	-0.16^{**}	(0.05)	-0.20^{**}	(0.04)	-0.20^{**}	(0.04)
$\gamma_{distance^2}$	0.002^{**}	(0.0006)	0.002	(0.0003)	0.002^{**}	(0.0003)
$\gamma_{distance,SouthEast}$			0.09^{**}	(0.03)		
$\gamma_{distance,MidAtlantic}$			0.09^{**}	(0.03)		
$\gamma_{distance,MidWest}$			0.09^{**}	(0.02)		
$\gamma_{distance,Central}$			0.08^{**}	(0.02)		
$\gamma_{distance,regions}$					0.08^{**}	(0.02)
$\pi_{age<25,outside}$	–	–			-1.80^{**}	(0.46)
$\pi_{25<age<60,outside}$	–	–			-0.04	(0.50)
$\pi_{age>60,outside}$	–	–			0.08	(0.38)
$\chi^2(r)$	0.62 (1)		14.2 (4)		8.7 (1)	
Observations	3121x7		3121x7		3121x7	

Table 13: The second column for each specification reports the standard errors which are calcuated to take into account the variance in the estimates which is due to simulation error. In addition, the standard errors allow for arbitrary correlation in the unobserved product characteristic, ξ_{fht}, across time. Day of week, market, and film fixed effects included in all specifications. Model (1) reports the results when only distance traveled is added to the model. The parameters are identified by assuming that the population living within five and ten miles of the theater is uncorrelated with the unobserved product characteristic. Models (2) and (3) report the results when the disutility of distance is allowed to vary by region of the county. The omitted region is the western region and the parameters are identified by assuming that the population living within five and ten miles of the theater is uncorrelated with ξ_{fht}. Model (3) allows the value of the outside good to vary systematically with the age group of the consumer. These parameters are identified using the three age moments described in the text. The $\chi^2(r)$ test statistics report the appropriate test of the over-identifying restrictions imposed on the model.

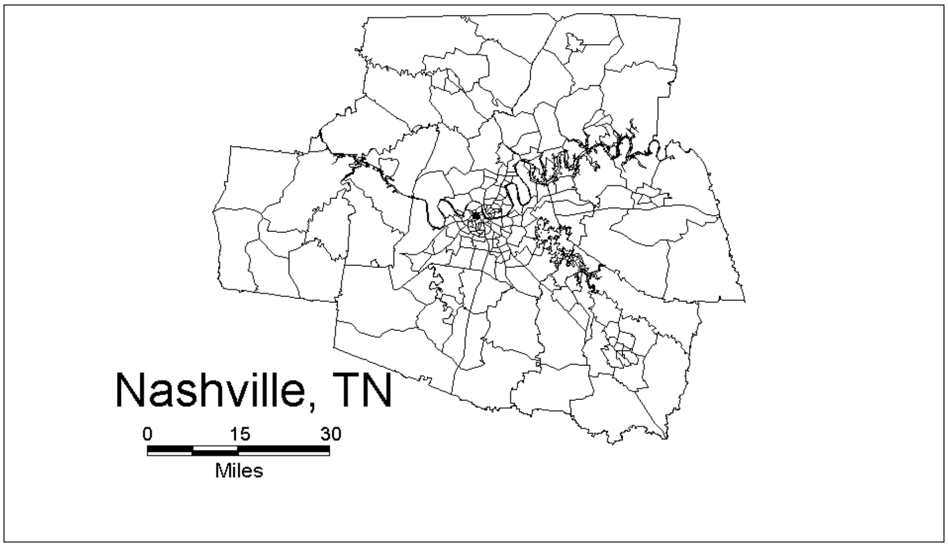

Figure 9: Census tracts in Nashville, TN. The bureau of the census partition each county into census tracts, each containing around 4000 people. Census file Stf3a reports the joint distribution of age by income and race for each census tract.

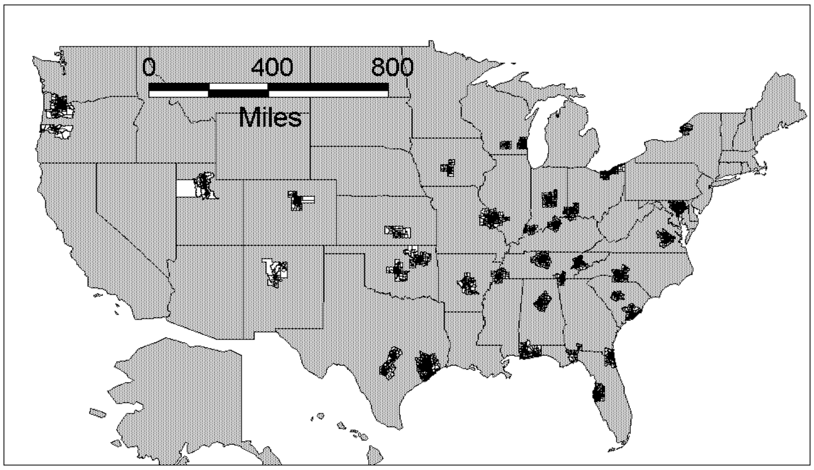

Figure 10: Sample coverage includes 36 market areas with 39.1 million people living in 14.8 million households.