Spatial Differentiation and Firm Entry: The Video Retail Industry*

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Abstract

This paper develops a static equilibrium model of market structure and product-type choice under imperfect information. The model is applied to location choices in geographic space. Estimation relies upon a unique data set, which combines detailed demographic data with geocoded firm-level data on realized entry and location choices from the video retail industry. Firms' endogenous location choices are formalized in a one-shot Bayesian game of asymmetric information about idiosyncratic sources of firm profitability. The model is solved numerically using a nested fixed-point algorithm.

The empirical results demonstrate the endogeneity of market structure and firm profitability: while favorable demand characteristics provide an incentive for stores to cluster together, the intensified competition associated with increased clustering drives profits down. The results also imply a large payoff to geographic differentiation since only the closest rivals exert strong competitive pressure on store profitability. Simulations and city-growth experiments underline the importance of incorporating product-type choices into the entry process. Allowing for spatial differentiation leads to a significant increase in the number of entrants into a market, in particular for cities made up of neighborhoods with distinctly different characteristics. Similarly, firms' abilities to capture localized market power by spatial differentiation are found to increase in the size of the market area, allowing for more entry in markets with larger spatial dispersion.

Keywords: Spatial differentiation, location choice, entry, retail markets

JEL Classification: L0, L1, L2, L4

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1 Introduction

Market activities typically occur at dispersed points in space due to the scattered locations of buyers and sellers. This geographic separation provides firms with a ready source of market power. Each firm will only find a limited number of competitors in its immediate neighborhood, and it will not compete as strongly with firms that are located further away due to the presence of transportation costs. Consumers will, when choosing among two identical sellers, prefer the one positioned most closely to their own location. Space can therefore be used to shield entrants from competition, and location becomes an instrument of strategic choice for the firm.

Previous empirical studies of entry (Bresnahan and Reiss 1991, Berry 1992) have recognized that a firm, when faced with the decision of entering a new market, must weigh the intensity of market rivalry against the available market demand. Firms' profits increase with the quantity demanded of their product; favorable demand conditions will, however, also attract a larger number of competitors. The increase in competition adversely affects profitability as more sellers share a common consumer base. By focusing on distinctly separate, well-defined markets, these authors do not have to account for degrees of competition that differ depending on where firms are located relative to each other within the market. Most real-world settings, however, do not conform to such specific conditions.

In larger, more geographically spread-out markets, competition between firms in a market is likely to vary with the distance between firms' locations. This applies in particular to retail markets, which are characterized by highly localized competition. Stores may have local market power despite a low concentration level at a national or even regional level. Optimal site selection becomes very important in such a setting and is driven by a trade-off between proximity to the customer and increased competition with rivals in these prime locations.

I study firms' joint entry and location decisions in larger, more urban retail markets, focusing on two aspects of firm interaction. First, I attempt to shed light on the rate at which competition within a market declines with distance. Second, I exploit the trade-off between customer base and intensity of competition to explain empirically the sorting pattern of firms into different locations within a city. This paper complements other recent applied work on the role of geography in microeconomic decision-making (Davis 2000, Thomadsen 1999). It differs, however, by focusing on the initial decision of where to open one's store instead of the subsequent decision of how much to charge the customer for the product.

The model presented in this paper is a static equilibrium model with asymmetric information. Firms are assumed to have private information over their own profitability. In making their location choices, they incorporate conjectures over their competitors' optimal location choices to maximize expected profits. The Bayesian framework entails notable advantages over its complete information counterpart that has been studied by Bresnahan and Reiss (1991) and Mazzeo (1998) in terms of its ease of verifying and computing equilibria. By introducing a solution concept based only on equilibrium beliefs, instead of pure location strategies, the framework allows firms' conjectures to be drawn on a realistic, large-dimensional set of product-type choices. Incorporating such a large-dimensional choice set would, at present, be infeasible in a complete information framework.

The model is applied to location choices and entry decisions in the video retail industry, which lends itself perfectly to the goals of this study. The transaction under consideration consists of the rental of a video tape at a video store. The good is therefore highly homogeneous, non-storable beyond the period of the rental, and relatively inexpensive. Customers physically go to the outlet and thereby bear the full transportation cost. Since the product itself is standardized, stores differentiate themselves in various ways, including inventory carried, differences in rental contracts concerning the rental period, and drop-off convenience. The main avenue of differentiation arises, however, from geographic dispersion. Due to small absolute differences in prices across stores, it is unlikely that customers will be willing to travel a long distance to carry out the rental. Therefore, the degree of competition between stores varies strongly by distance.

The extent and role of geographic differentiation is of importance to antitrust policy makers when investigating the potential effects of, for example, a merger on long-run entry dynamics in an industry. An assessment of how the degree of competitive interaction changes with distance can be used to more reliably characterize rivalry within a market. Predictions of the number of competitors expected to operate in a given market in equilibrium provide further insights into the nature of competition that is actually taking place in the market. The results presented in this paper indicate that firms use spatial differentiation effectively to shield themselves from a large fraction of competitors in the market. Varying intensities of competition across the product space help to explain empirical patterns of location choices found in the data, which shows clustering of firms as well as spreading into less attractive locations. The model is then used to investigate the contributions of two dimensions of the product space to the entry process. The expected number of entrants into a market is a function of both population size and its distribution in the market, as well as the market's overall spatial dispersion. Ignoring location choice as an important part of the entry process is shown to lead to a significant understatement of the number of entrants supported by a market, in particular in markets of diverse demographic characteristics and large market areas. Evaluating the degree of rivalry in a market based on conventional entry models that ignore product differentiation, therefore, biases results towards concluding that competition is more intense than is accurate.[1]

This paper is organized as follows: Section 2 contains a brief literature review to set-up the context for the present paper. Section 3 presents a simple model of location choice and market structure, while section 4 describes the data set used for estimation. In section 5, I outline the estimation routine used to estimate the model from section 3 and present some base-line results. These results are then incorporated into out-of-sample experiments to compare predictions from the current model with a conventional entry model. I investigate both models' implications for the number of competitors supported by a variety of market structures. Section 6 concludes and outlines a number of extensions to the present work.

2 Literature Review

Recent theoretical work in industrial organization has drawn upon the multi-stage game as an equilibrium framework for analyzing various aspects of the firm-level decision making process. Relying upon primarily cross-sectional data, these models have been empirically estimated to analyze firm entry and investment decisions, as well as the ensuing price and non-price competition. Since prior investment decisions require a commitment of assets and resources, the outcome of these decisions is, in general, taken as a fixed input into the competition stage where payoffs are determined. The work presented in this paper draws upon both of these strands of the literature, focusing on the initial investment decisions, such as entry into a given market, as well as the actual competition stage, where price and non-price instruments, such as quality levels, are set in determining firm profits.

[1] A recent example of an antitrust case concerned with local market power is the failed merger between Staples and Office Depot. The FTC challenged the acquisition of Office Depot by Staples based on the potential anticompetitive effects of the merger, presenting evidence that compared the firms' competitive conduct across several cities. The report's main conclusion was that cities in which only one office superstore operated were essentially "non-competitive zones" while competition intensified only as at least two superstores operated in the market. See Baker (1997).

2.1 Entry and Market Structure

A series of papers by Bresnahan and Reiss (1988, 1991) and Berry (1992) focuses on the competitive effects of entry in situations where firms' price-cost margins are unknown. The authors recognize the endogeneity of concentration and profits in oligopolistic markets; firms enter a certain market because their profit margins are sufficient to cover fixed costs of operating, however, these margins are driven down with each additional entrant.

Bresnahan and Reiss relate shifts in market demand to changes in the equilibrium number of firms in order to measure the decline in profits with additional competition. The authors apply their methodology to a set of small, isolated, rural retail and professional markets, allowing them to abstract from other facets of competition. The markets under consideration consist of very homogeneous product markets in which geographic differentiation is likely to be negligible due to the small market size of on average 3,740 people. Most real-world settings, however, do not satisfy the stringent criteria imposed by the authors upon their sample cities. In larger, more geographically spread-out markets, competition between firms is likely to vary with the distance between firms' location, as well as other means of product differentiation.

Berry explicitly recognizes the importance of differences between firms as an additional force besides market-level demand and supply in driving firm-level profitability. His focus on entry into oligopolistic airline markets naturally entails an atomistic market definition based on airlines airport presence. Similar to Bresnahan and Reiss, Berry's (1992) study incorporates the simultaneity of profitability and market structure while allowing for heterogeneity in observed and unobserved firm costs. The results from these studies confirm the premise of endogeneity of profits and market structure with declining profits as competition intensifies.

2.2 Spatial Competition

The recent industrial organization literature has made significant progress in assessing the role of product differentiation in price and profit determination within concentrated industries. Drawing on seminal work by McFadden (1978) and others, Berry, Levinsohn, and Pakes (1995) as well as Goldberg (1995) develop random utility models of differentiated product demand using the automobile industry as a case study. Subsequently, these techniques have been applied to a variety of industries, ranging from cereals (Nevo 1998) to personal computers (Bresnahan, Stern, and Trajtenberg 1998). By projecting what is often a large number of products onto a space of characteristics, demand elasticities between these products can be estimated in order to analyze issues regarding market power, innovation, and welfare.

The increased availability of software and detailed data on the geographic layout of the US landscape down to extremely small, disaggregated spatial units has allowed for an extension of the techniques put forth in Berry, Levinsohn, and Pakes to study spatial competition. Davis (2000) and Thomadsen (1999) estimate differentiated product demand systems for two retail industries, movie theaters and fast food restaurants, respectively. The authors incorporate geography into their framework by allowing transportation costs between supplier and consumer location to negatively affect consumer utility from frequenting a given supplier. Taking firms' locations as predetermined, the authors focus on the role of geographic differentiation in relaxing price competition between outlets and on the welfare effects of relocating outlets.

2.3 Product Differentiation and Market Structure

A small literature investigates the joint entry and product choice decisions by firms, drawing upon elements of the research discussed above. Toivanen and Waterson (1998) study the effects of existing market structure on new entry in the UK fast food industry, focusing on differences in entry decisions related to the entrant's chain affiliation. Stavins (1995) analyzes the relative product-space location choices of new model entrants in the personal computer industry while accounting for market and firm characteristics. Neither study explicitly models the endogeneity of the product-type and entry choice. Mazzeo (1998) develops an equilibrium model of quality choice and market structure, which is applied to the motel industry. The perfect foresight character of his model makes it difficult, however, to extend the model to a large number of different product types. Even with three quality levels, estimation of the model becomes burdensome due to the large number of profit constraints that have to hold in equilibrium. The model presented in the next section circumvents this limitation by allowing firms to possess some level of private information about their own profitability. The resulting equilibrium conditions are less stringent, facilitating the estimation of a model with many product types. The presented model draws upon recent research from the public finance literature, which estimates endogenous sorting models of residential community choice. In equilibrium, these models allow an individual's preferences over communities to be affected by the characteristics of other individuals who also choose the community (Bayer 1999, Timmins 1999).

3 Model

3.1 Motivation

Market structure and location choice are ideally the outcome of a fully specified model of firm profit maximization. While entry into operation at a certain location involves fixed costs of entry, the entry decision is by no means irreversible. A firm's location and entry choice will be determined by long-run expectations of profitability and market demand and may involve strategic considerations such as the foreclosure of a given market or location from rivals. The appropriate framework in which to analyze the given problem would therefore be a dynamic model of firm entry and market structure where the state-space includes all location choices available to the firm in a market, accounting for competitors' choices over the same state space. The continuous nature of space requires some discretization to give meaning to the concept of a location. Even with relatively small markets, a coarse definition of location, and a small number of potentially active competitors, this sort of dynamic model presents severe challenges in terms of its computational burden. In addition, the required data on quantities, prices, and costs are, in the case of retail markets dominated by chains, often unavailable at the outlet level. Similarly, the retail sector's production technology, inputs into production, and cost structure are not easily quantifiable or well defined.

The model presented in the following section abstracts from this ideal model in a number of ways. Its advantage lies primarily in the relative ease of computing the equilibrium strategies and parameter estimates. This computational ease comes at a cost, however, as the model is based on relatively strong functional form assumptions and a partial equilibrium set-up. In future work, I will estimate a more fully specified model of sequential entry, in which firms' location choices are conditioned on the history of the entry-generating process and firms' expectations of their rivals' future actions. Contrasting the results from such a model to the corresponding results from the static equilibrium model will provide insights into the importance of firms' forward-looking behavior in driving industry conduct.

The market, the unit of observation used for the analysis, is a city divided into non-overlapping cells or locations. For simplicity, entry and location choice decisions across different markets are assumed to be independent. I therefore do not consider whether entering into one market might affect a firm's profitability in other, nearby markets. Primarily chain stores may, however, investigate the potential for cannibalization of revenues in existing stores when choosing the optimal location for a new outlet. At the beginning of the period, each firm makes its joint operation and location choice based on its expected post-entry profits. Post-entry profits are driven by two opposing forces. The natural advantages of a location in the form of favorable demand conditions provide an incentive for firms to cluster together. Increased concentration in a particular location or nearby locations, however, has adverse consequences for store profits due to business stealing effects as well as intensified competition in post-entry market interactions.

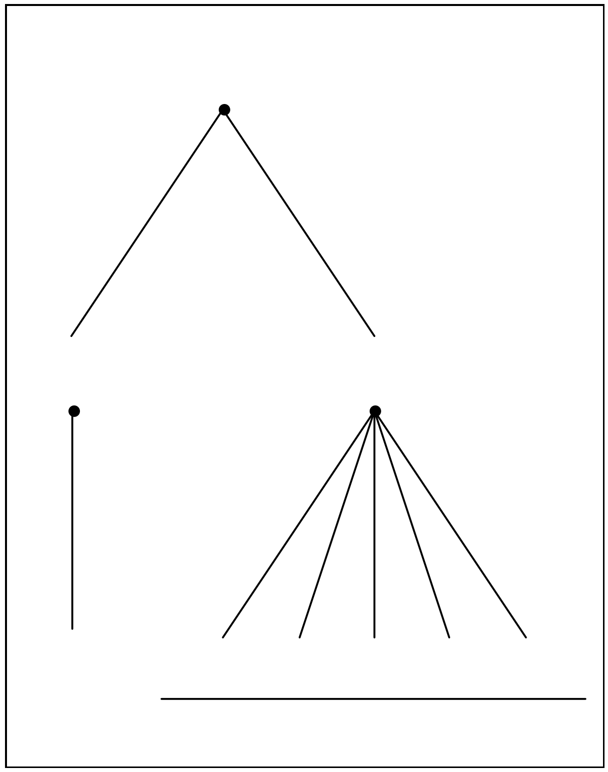
Firms' profits are thus specified as a function of cell and market-level variables, as well as the equilibrium location choices by all actors in the market including the firm itself. Pay-off functions are furthermore allowed to differ by firm and by location. Systematic differences among firms may be responsible for explaining why one firm operates more profitably in a given location than its competitors. Casual evidence suggests, for example, that smaller, single-outlet video stores are, on average, a better fit to primarily residential locations, where residents are willing to forego some of the larger selection of a chain-affiliated store in return for the convenience and more personal service of a "Mom and Pop" store. Unsystematic, firm-specific characteristics, such as the staff's managerial talent, customer service, or inventory maintenance may be even more crucial in driving firm profitability. This source of firm profitability is assumed to be private information, which is ex-ante only observed by the firm itself, but not by its competitors or the econometrician. A firm's managerial talent, for example, can be more easily assessed by the firm itself than by its competitors, especially in the case of single-location or franchised outlets. Competitors, on the other hand, will take longer to learn about the firm's intangible assets, as they have to separate the role of those assets in a store's success from other related profit shifters.

3.2 Set-up

In the ensuing Bayesian game, firms' entry and location choices are modeled as a nested discrete choice problem. A set of potential entrants, amounting to a total of $N^{\max}$ firms, considers entry and location choice into a given market m. At the beginning of the period, the $N^{\max}$ firms simultaneously choose whether or not to enter the market and, conditional on having decided to enter, their optimal location among the L geographic subunits of the market. The first dimension of the choice set is indexed by c, with $c = \{in, out\}$, whereas choices in the lower nests are indexed by $i = 0, 1, ..., L$, making up the set of possible locations for active and inactive firms. Each firm makes its joint entry and location choice decision based on its expected post-entry profits. Figure

3.1 displays the decision-making tree.

Figure 3.1: Joint Entry and Location Choice as a Two-Stage Process



Firm a's pure location strategy, with $a = 1, ..., N^{\max}$, is denoted as $\mathbf{s}^a$, where $s_i^a = 1$ if location i is chosen, 0 otherwise and exactly one cell is chosen.[2] The choice of location is driven by a pay-off comparison from locating in each of the market cells i, $i = 1, ..., L$, as well as choosing not to enter, indexed by $i = 0$. Upon entry, firm a's pay-off in location i of market m is assumed to take the following, tractable form:

$$\begin{aligned} \Pi_{ci}^{am} &= \xi^m + \mathbf{X}_i^m \boldsymbol{\beta} + h(\theta_{ii}, n_i^m) + \sum_{j \neq i} \mathbf{X}_j^m \boldsymbol{\beta} + \sum_{j \neq i} h(\theta_{ij}, n_j^m) + \eta_{ci}^{am} \\ &= \overline{\Pi}_i^m + \eta_{ci}^{am} \end{aligned} \tag{3.1}$$

where the variables denote:

ξ^m unobserved (by researcher) market-level fixed effect

[2]For a more detailed exposition of Bayesian games and equilibria see Fudenberg and Tirole (1991), pp. 209-241.

$\mathbf{X}_i^m$ vector of demand characteristics specific to location i

n_i^m number of competitors operating in location i in equilibrium

θ_{ij} effect of number of competitors operating in location j on profitability from operating in location i

$h(.,.)$ function decreasing in n_i^m

η_{ci}^{am} idiosyncratic component of firm a's profits from operating in location i

The mean profitability from not entering, $\overline{\Pi}_0^m$, is normalized to zero across firms and markets. Firm a's type $\boldsymbol{\eta}^a$ over locations i, $i = 0, ..., L$, is determined by the heterogeneous component of the pay-off function, which measures the above described firm- and location-specific contributions to profits. For the sake of computational tractability, I assume that players' types, $\{\boldsymbol{\eta}^a\}_{a=1}^{N^{\max}}$, are independent, identically distributed draws from a type-B multivariate generalized extreme value distribution.[3] The similarity coefficient ρ causes the idiosyncratic profitability draws across market locations to be correlated relative to the no-entry option. This correlation thus provides a measure of the degree of asymmetric information over firms' profitability. In the limit, as ρ grows to infinity, shocks across locations are perfectly correlated and concentrated at the distribution's mean. In this case, there is no imperfect information about rivals' profitability and the game reduces to one of perfect information. While the underlying distribution of profitability draws is common knowledge to all firms in the market, the firm and location-specific realization of the shock is only observed by the firm itself. Firms that decide not to enter the market earn only their idiosyncratic profitability draw, corresponding to the option value of expending their managerial talent on different pursuits.

The assumption of i.i.d. draws has some strong implications for firm profitability. Firm profitability in a given location is uncorrelated across firms. Thus, the current set-up does not allow for systematic firm heterogeneity of the form discussed above, where certain retail stores, such as chain stores, always operate more profitably in a given location than the remaining competitors. Examples of such instances are easy to come by, however; consider a retail-intensive commuter road where

[3] The general formula for the cumulative distribution function of the type B multivariate extreme value distribution is:

$$F(\eta_{ic}^m) = \exp\{-\gamma_{in}(\sum_{i=1}^{L} \mathrm{e}^{-\rho\eta_{i,in}^m})^{1/\rho} - \gamma_{out}\mathrm{e}^{-\eta_{i,out}^m}\}$$

$<\gamma_c>$, which determines the distribution's position, is captured by the market-level fixed effect, ξ^m, for the <*in*> choice and is normalized to zero for the <*out*> choice. The notation adopted in this exposition follows Morey (1999). In McFadden's (1978) original notation, $1/(1-\sigma)$ corresponds to the similarity coefficient ρ used in the present work. For details on the derivation of the multinomial and nested Logit models and their properties in the context of utility maximization, see Anderson, de Palma, and Thisse (1992), pp. 39-62.

customers care primarily about speedy, routine service and convenience. These are characteristics that are more readily associated with the shopping experience offered by chain stores. Such sources of systematic differences among firms, primarily along the lines of chain affiliation as well as degree of specialization of the products carried in the store, will be addressed in future work.

Since profitability draws are uncorrelated across players, knowing its own type $\boldsymbol{\eta}^a$ does not allow firm a to infer the types of competitors $\{\boldsymbol{\eta}^{-a}\}$ it faces in the market, where $\boldsymbol{\eta}^{-a} = \boldsymbol{\eta}^1, \boldsymbol{\eta}^2,...,\boldsymbol{\eta}^{a-1}, \boldsymbol{\eta}^{a+1},...,\boldsymbol{\eta}^{N^{\max}}$. Instead, it forms expectations about its rivals' optimal location choices based on the distribution of their types, $f(\boldsymbol{\eta})$. Integrating over the distribution of its competitors' types $\boldsymbol{\eta}^{-a}$ yields its expectation of the equilibrium firm distribution across locations, $\mathbb{E}^a[\mathbf{n}_i(\mathbf{s}^a, \mathbf{s}^{-a})] = \{\mathbb{E}^a[n_0(.)], ..., \mathbb{E}^a[n_L(.)]\}$. The firm then makes its own location choice by comparing expected profits in each location.:

$$\mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_i^a] = \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\xi + \mathbf{X}_i\boldsymbol{\beta} + h(\theta_{ii}, n_i) + \sum_{j\neq i}\mathbf{X}_j\boldsymbol{\beta}_j + \sum_{j\neq i}h(\theta_{ij}, n_j) + \eta_{ci}^a] \tag{3.2}$$

where the market superscripts m have been suppressed for expositional ease and η_{ci}^a is the observed realization of firm a's own type.

To render the model more tractable and reduce the number of parameters to be estimated, I make the following simplifying assumptions. First, I assume that firms and customers located in different cells, j and k, but at the same distance, $\overline{\mathbf{d}}$, from location i will have the same competitive impact on the profitability of firms operating in location i. In the notation above, this assumption implies that $\theta_{ij} = \theta_{ik}$ if $d_{ij} = d_{ik}$, where d_{ij} denotes the distance in some metric between locations i and j. This assumption ensures that an identical profit function can be imposed upon every location in the market and across markets. Furthermore, I assume that the competitive impact enters firm profitability linearly so that $h(\theta_{ij}, n_j) = \theta_{ij}n_j$. As a result of these two assumptions, all firms on a concentric circle from location i will exert the same competitive pressure on firms in cell i.[4] The following exposition categorizes competing stores into three groups according to distances from cell i, and the competitive impacts these stores have on profits from operating in i varies accordingly. The model can, however, be easily adjusted to allow for finer gradations of competition rings at various distances.

[4]Note some of the potential problems with this approach: the competitive pressure exerted by two firms located in a single location to the North of i will be the same as the competitive pressure of two firms, of which one operates in the cell directly North of i and one in the cell directly South of i. Ideally, the first scenario would be more attractive to firm a than the second; however, in the current treatment of competitive impacts, there will be no difference.

Based on two distance rings, equation 3.1 can be rewritten as:

$$\begin{aligned}
\mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi^a_{ci}(\mathbf{s}^a, \mathbf{s}^{-a}, \boldsymbol{\eta}^a)] &= \xi + \mathbf{X}_{0i}\boldsymbol{\beta}_0 + \mathbf{X}_{1i}\boldsymbol{\beta}_1 + \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \theta_0 E[n_i] + \theta_1 E[r_{1i}] + \theta_2 E[r_{2i}] + \eta^a_{ic} \\
&= \mathbb{E}^a[\overline{\Pi}^a_i] + \eta^a_{ci} \qquad (3.3)
\end{aligned}$$

In this simplified set-up, variables have been combined as follows:

θ_0	competitive impact of firms located in i (including firm a) at distance $\overline{\mathbf{d}}^0 = 0$
θ_1, θ_2	competitive impact of firms located at a distance $\overline{\mathbf{d}}^1$ and $\overline{\mathbf{d}}^2$, respectively, from cell i, with $\overline{\mathbf{d}}^1 < \overline{\mathbf{d}}^2$
$\mathbf{X}_{0i}$	vector of observed demand characteristics and cost shifters specific to location i
$\mathbf{X}_{1i}$, $\mathbf{X}_{2i}$	demand characteristics of locations at a distance $\overline{\mathbf{d}}^1$ and $\overline{\mathbf{d}}^2$, respectively, from cell i
r_{1i}, r_{2i}	competitors located at a distance $\overline{\mathbf{d}}^1$, $\overline{\mathbf{d}}^2$ from cell i: $r_{1i} = \sum_{j \neq i} \mathbf{1}^{\phi}_{ij} n_j \quad \forall j \neq i$, $\mathbf{1}^{\phi}_{ij} = 1$ if $d_{ij} = \overline{\mathbf{d}}^1$, 0 otherwise; $r_{2i} = \sum_{j \neq i} \mathbf{1}^{\psi}_{ij} n_j \quad \forall j \neq i$, $\mathbf{1}^{\psi}_{ij} = 1$ if $d_{ij} = \overline{\mathbf{d}}^2$, 0 otherwise

3.3 Equilibrium

3.3.1 Equilibrium Location Choices

In equilibrium, firms choose strategies $\{\mathbf{s}^1(\boldsymbol{\eta}^1)^*, \mathbf{s}^2(\boldsymbol{\eta}^2)^*, ..., \mathbf{s}^{N^{\max}}(\boldsymbol{\eta}^{N^{\max}})^*\}$ such that, for each firm a and each of its possible types $\boldsymbol{\eta}^a$, strategy $\mathbf{s}^a(\boldsymbol{\eta}^a)^*$ maximizes its expected pay-off across locations, including the no-entry option. Analyzing first the location decision, assume that a total of $\widehat{N}$ firms has decided to enter the market, firm a being one of them. Its equilibrium location strategy, conditional upon having made the entry decision, maximizes its expected pay-off across market cells:

$$\mathbf{s}^a(\boldsymbol{\eta}^a)^* \in \arg\max_{\mathbf{s}^a} E_{\boldsymbol{\eta}^{-a}} \boldsymbol{\Pi}^a(\mathbf{s}^a, \mathbf{s}^{-a}(\boldsymbol{\eta}^{-a})^*, \boldsymbol{\eta}^a) \qquad (3.4)$$

Each of the remaining $(\widehat{N} - 1)$ entrants will choose the location that, conditional on its type, maximizes expected profits. Since firm a knows only the underlying distribution of its competitors' types, each rival is, in firm a's eyes, identical. Let firm b be one such representative competitor. Firm a employs its knowledge of the distribution of its competitors' idiosyncratic, independent profitability draws, $f(\boldsymbol{\eta})$, to derive a probability distribution of firm b's location choice over the L

locations. Firm a's conjecture of the probability that firm b will choose location i equals:

$$\begin{aligned} p^{a,b}(l^b = i \,\big|\, c^b = in) &= \Pr(s_i^b(.)^* = 1) = \Pr(\mathbb{E}_{\boldsymbol{\eta}^{-b}}\Pi_i^b(\eta_{ci}^b) \geq \mathbb{E}_{\boldsymbol{\eta}^{-b}}\Pi_j^b(\eta_{cj}^b),\ \forall\ j \neq i) \\ &= \Pr(\mathbb{E}^b[\overline{\Pi}_i(\mathbf{s}^{-b})] + \eta_{ci}^b \geq \mathbb{E}^b[\overline{\Pi}_j(\mathbf{s}^{-b})] + \eta_{cj}^b,\ \forall\ j \neq i) \end{aligned} \tag{3.5}$$

The assumption of a type-B multivariate generalized extreme value distribution for firm b's types gives rise to the traditional multinomial Logit probability vector over the lower-nest location choice set, adjusted for the locations' within-nest correlation, ρ. Thus, firm a conjectures that its rival b will choose location i with probability:

$$p^{a,b}(l^b = i \,\Big|\, c^b = in) = \frac{\exp(\rho \mathbb{E}^b \overline{\Pi}_i^b)}{\sum\limits_{k=1}^{L} \exp(\rho \mathbb{E}^b \overline{\Pi}_k^b)} \tag{3.6}$$

Since each of the idiosyncratic profitability shocks comes from the same distribution, firm a's conjecture over its competitors' optimal location choice probabilities $\mathbf{p}^{a,b}$ will be the same for each of its $(\widehat{N}-1)$ competitors, simplifying to $\mathbf{p}^a$. Consequently, the total number of competitors – excluding itself – that firm a expects to face in location i equals:

$$\mathbb{E}^a[n_i^{-a}] = \sum_{b \neq a} p_i^{a,b} = \sum_{b \neq a} p_i^a = (\widehat{N}-1)p_i^a \tag{3.7}$$

In computing the expected pay-off from operating in a given location i, firm a has to also take into consideration its own impact on profits in that cell. Since there is no uncertainty about its own type, the total expected number of competitors in cell i includes itself, such that $\mathbb{E}^a[n_i] = \mathbb{E}[n_i^{-a}] + 1 = (\widehat{N}-1)p_i^a + 1$. Firm a's resulting expected pay off in cell i is given by:

$$\begin{aligned} \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{ci}^a] &= \xi + \mathbf{X}_{0i}\boldsymbol{\beta}_0 + \mathbf{X}_{1i}\boldsymbol{\beta}_1 + \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \theta_0[(\widehat{N}-1)p_i^a + 1] + \theta_1[\sum_{j \neq i} \mathbf{1}_{ij}^{\phi}(\widehat{N}-1)p_j^a] \\ &\quad + \theta_2[\sum_{j \neq i} \mathbf{1}_{ij}^{\psi}(\widehat{N}-1)p_j^a] + \eta_{ci}^a \\ &= \mathbb{E}^a\overline{\Pi}_i^a + \eta_{ci}^a \end{aligned} \tag{3.8}$$

Analogously to firm a, the remaining competitors make their conjectures over firm a's optimal strategy. Since firm a's type, $\boldsymbol{\eta}^a$, is also a Logit draw, firm b's expectation of the probability distribution of firm a's location choice is given by an expression similar to 3.5:

$$\begin{aligned} p_i^{b,a} &= \Pr(\mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{ci}^a] \geq \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{cj}^a]\ \ \forall\ j \neq i) = \frac{\exp(\rho \mathbb{E}^a \overline{\Pi}_i^a)}{\sum\limits_{k=1}^{L} \exp(\rho \mathbb{E}^a \overline{\Pi}_k^a)} \\ \forall\ i &= 1, ..., L \text{ and } \forall\ b = 1, ..., \widehat{N},\ b \neq a \end{aligned} \tag{3.9}$$

The unobserved profitability index is the only source of firm heterogeneity currently incorporated into the model. Therefore, in a symmetric equilibrium, firm a's conjecture of the probability that each of its competitors will enter a given location has to be equal to the conjecture maintained by its rivals of the probability that firm a itself will enter that location. In the above notation, we have that $(\mathbf{p}^{b,a})^* = (\mathbf{p}^{a,b})^* = \mathbf{p}^*$. Firm a's probability vector over all locations i is consequently defined recursively by the following set of equations:

$$p_i^* = \frac{\exp(\rho(\xi + \mathbf{X}_i\boldsymbol{\beta} + \theta_0 + (\widehat{N}-1)(\theta_0 p_i^* + \theta_1 \sum_{j\neq i} \mathbf{1}_{ij}^{\phi} p_j^* + \theta_2 \sum_{j\neq i} \mathbf{1}_{ij}^{\psi} p_j^*)))}{\sum_{k=1}^{L} \exp(\rho(\xi + \mathbf{X}_k\boldsymbol{\beta} + \theta_0 + (\widehat{N}-1)(\theta_0 p_k^* + \theta_1 \sum_{j\neq k} \mathbf{1}_{jk}^{\phi} p_j^* + \theta_2 \sum_{j\neq k} \mathbf{1}_{jk}^{\psi} p_j^*)))} \tag{3.10}$$

where all exogenous choice characteristics have been combined into the single term $\mathbf{X}\boldsymbol{\beta}$. Equation 3.10 is part of a system of L equations, which make up a fixed-point mapping from firm a's conjecture of its competitors' strategies into its competitors' conjecture of the firm's own strategy. Based on the vector of equilibrium location choice probabilities, firm a will enter the market if expected profits in at least one location exceed the outside option's pay-off, such that

$$\begin{aligned} (s_i^a)^* &= 1 \Leftrightarrow \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{ci}^a] \geq \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{cj}^a] \;\forall\; j \neq i, j = 0, 1, ...L \\ \mathbb{E}_{\boldsymbol{\eta}^{-a}}[\Pi_{ci}^a] &= \xi + \mathbf{X}_i\boldsymbol{\beta} + \theta_0 + (\widehat{N}-1)(\theta_0 p_i^* + \theta_1 \sum_{j\neq i} \mathbf{1}_{ij}^{\phi} p_j^* + \theta_2 \sum_{j\neq i} \mathbf{1}_{ij}^{\psi} p_j^*) + \eta_{ci}^a \end{aligned} \tag{3.11}$$

The existence of at least one equilibrium for the model follows immediately from Brouwer's Fixed Point Theorem. Equation 3.10 sets up a continuous mapping from the L-dimensional simplex into itself. An important role is played by the asymmetric information component of the model. Since firms need to integrate over competitors' location choices, their rivals' discrete actions are transformed into smooth predicted location probabilities. Thus, firms' own location choice probabilities are contained in the simplex and are continuous in their competitors' expected behavior.

Uniqueness of the equilibrium is harder to establish and will only hold in certain empirical settings. As the lay-out and size of markets change, different profit functions result. Each of the markets used in the empirical analysis is made up of a unique lay-out of cells and the location of cells relative to each other differs by market. Therefore, equilibrium properties need to be established separately for each of the markets. An analytic solution to the fixed point algorithm does not exist for cities made up of even as little as five cells. Numerical simulations can be used, however, to provide insights into the conditions that the data needs to satisfy for the equilibrium to be unique.

The equilibrium described by equation 3.10 can be computed numerically based on the method of successive approximations. Using an arbitrary probability vector as starting values for the equilibrium location choice probabilities, the fixed point is found by successively improving upon the initial guess until $[\frac{\exp(\rho\overline{\Pi}_1(\widetilde{\mathbf{p}}))}{\sum_k \exp(\rho\overline{\Pi}_k(\widetilde{\mathbf{p}}))}, \ldots, \frac{\exp(\rho\overline{\Pi}_k(\widetilde{\mathbf{p}}))}{\sum_k \exp(\rho\overline{\Pi}_k(\widetilde{\mathbf{p}}))}]'$ results in $\widetilde{\mathbf{p}}$. The existence of a unique equilibrium can be established numerically if successive approximations always converge to the same solution, independent of the initial starting values.

Relying upon actual sample data as well as simulated data, I investigate the equilibrium properties with respect to the following aspects: variation in the exogenous, cell-level covariates, X; size of the location choice set, L; and size of the similarity coefficient between η-draws, ρ. The numerical exercises show that relatively weak constraints need to be imposed upon the data and parameter values to ensure a unique equilibrium. These constraints are in general satisfied by the markets in the sample under a wide range of parameter values, in particular for the presumed, negative spillovers associated with clustering that arise in this application.

In particular, the simulations imply that a unique solution to the fixed point algorithm exists provided there is a sufficient number of location choices and variation in observed cell-level demographics. If cells were identical, distinguishing between choices based on pay-off differences would be more difficult and multiple sets of equilibrium location probabilities could easily arise. The specification of the profit function, which combines the competitive effects of firms located within a given distance band into one uniform impact, does not impair the uniqueness properties of the equilibrium. A given cell will not fall into the same distance ring relative to all other locations in the market. Further, the locations that are combined into one distance ring vary depending on the reference location's placement within the city. Thus identifying unique location-choice probabilities for all cells in a market is feasible.

Last, related research (Mazzeo 1998) has shown that the complete information counterpart to the model presented here does not necessarily have a unique Nash equilibrium solution. Likewise, the fixed point algorithm described above may break-down as the similarity coefficient ρ becomes large. As ρ grows, the correlation coefficient between η-draws, which equals $1 - \frac{1}{\rho^2}$,[5] approaches one. With perfect correlation, firm a can perfectly deduce its competitors' profitability, so that the game reduces to one of perfect information. A computation of the equilibrium conjectures for the

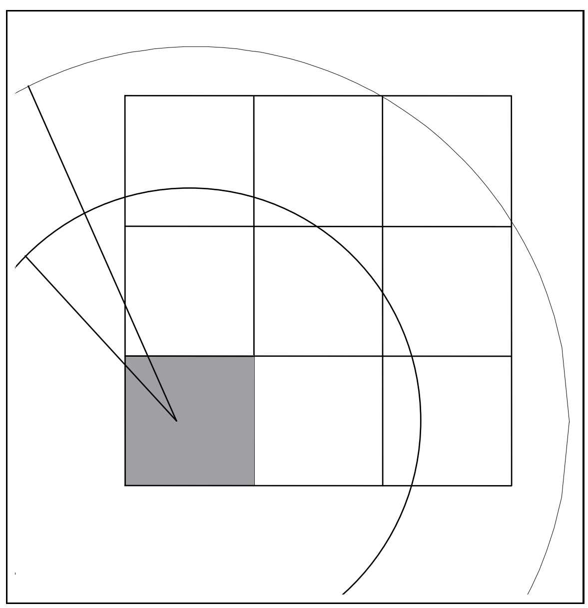
[5] See Amemiya (1985), pp. 300-306.

actual data, which satisfies the remaining regularity conditions discussed above, shows, however, that the equilibrium is insensitive to the choice of starting values even for correlation coefficients on the order of 0.975.[6] Very small levels of incomplete information are thus sufficient to guarantee unique location conjectures. Future work will investigate these equilibrium properties in greater detail relying upon more systematic Monte Carlo evidence regarding the degree of variation in observable demographics necessary to support a unique equilibrium set of location probabilities under alternative values for the competitive effects, θ.

3.3.2 Illustration

As an illustration, figure 3.2 depicts a square market made up of nine locations. Locations are

Figure 3.2: Impact on Profits of Competitor Location: Illustration



grouped into three categories according to their distance from the location that is being considered by the firm. The competitive impact exerted by firms operating in the market depends on whether they operate within the same cell, in a cell at a distance $\overline{\mathbf{d}}^1$, or in a cell at a distance $\overline{\mathbf{d}}^2$. Immediate competitors of a firm located in cell seven in figure 3.2, for example, are other firms choosing that

[6] Solving for the equilibrium under an even larger correlation coefficient is computationally infeasible since computing precision is limited with respect to the exponential involved in computing equilibrium probabilities. The exact degree of asymmetric information necessary for the location conjectures to be unique can, therefore, not be ascertained.

same location, adjacent competitors would be firms located in cells four, five, and eight, while the most distant competitors would be located in cells one, two, three, six, or nine. Based on equation 3.8, the common component of equilibrium expected profits, $\mathbb{E}_{\boldsymbol{\eta}}[\overline{\Pi}_i]$, for a firm entering into location seven would thus be given by:

$$\mathbb{E}_{\boldsymbol{\eta}}[\overline{\Pi}_7] = \xi + \mathbf{X}_7\boldsymbol{\beta} + \theta_0 + (\widehat{N} - 1)(\theta_0 p_7^* + \theta_1(p_4^* + p_5^* + p_8^*) + \theta_2(p_1^* + p_2^* + p_3^* + p_6^* + p_9^*)) \quad (3.12)$$

In the above specification, $\mathbf{X}_7$ contains demand shifters specific to location 7, such as population or per capita income, as well as demand from locations at a distance $\overline{\mathbf{d}}^1$ and $\overline{\mathbf{d}}^2$, including total population at a distance $\overline{\mathbf{d}}^1$, which equals the sum of the population of cells four, five, and eight, or average per capita income of adjacent cells. Assuming that the competitive impact of firms in immediately neighboring cells, θ_1, exceeds the one of more distant firms, θ_2, the appeal of cell 7 lies primarily in its placement at the edge of the city and small set of immediately adjacent locations, which could serve competing firms. A firm located in cell 5, on the other hand, will have many close-by competitors, exposing it to stronger competition than a firm located on the city's fringe. At the same time, location 5 is more attractive since it grants easy access to most of the consumers in the market living in the neighboring as well as the own location. The resulting equilibrium firm location pattern is determined by this trade-off between demand and competitive pressures.

3.3.3 Accounting for the Endogeneity of the Competitor Pool in Estimation

In a free-entry equilibrium, the number of entrants into a market is driven by a no-profit condition. Active competitors earn non-negative profits while any additional entrant would earn negative profits. The total number of firms supported by a market is a function of that market's underlying attractiveness, which is in part captured by its locations' demographic make-up. These observable demographics will not reflect all cost and demand factors influencing firms' profitability. Unobservable sources of revenue and cost are assumed to be captured by a market-level fixed effect, ξ^m, whose level scales market attractiveness relative to the remaining markets in the sample. For video stores, this may reflect the local populations' general taste for film, the presence of alternative entertainment options in the city, such as movie theaters, or other regional differences between markets. The number of entrants that can be supported by a given market is then, in part, determined by ξ^m: a very profitable market with a high unobservable ξ^m will support a larger number of entrants. The larger number of active rivals then drives the market's average profit levels down to be in par with the remaining markets.

While assumed to be known to the firm, the researcher does not observe the market-level fixed effects. Instead, a flexible functional form assumption is imposed upon the distribution of ξ^m:

$$\xi^m \sim i.i.d.\ N(\mu, \sigma^2) \tag{3.13}$$

In the absence of systematic differences between firms, all firms are observationally identical to the econometrician and have equal probabilities of entering a given market. The econometrician's prediction of the number of total entrants that is consistent with the assumption of i.i.d. extreme value profitability shocks thus reduces to:

$$\begin{array}{lcl} \widehat{N} & = & N^{\max} \cdot \Pr(c = in) \\ \Pr(c = in) & = & \frac{\exp(\xi) I^{in}(\widehat{N})}{1+\exp(\xi) I^{in}(\widehat{N})} \\ I^{in}(\widehat{N}) & = & [\sum_{i=1}^{L} \exp\{\rho(\mathbf{X}_i \boldsymbol{\beta} + \theta_0 + (\widehat{N}-1)(\theta_0 p_i^* + \theta_1 \sum_{j \neq i} \mathbf{1}_{ij}^{\phi} p_j^* + \theta_2 \sum_{j \neq i} \mathbf{1}_{ij}^{\psi} p_j^*))\}]^{1/\rho} \end{array} \tag{3.14}$$

Equation 3.14 can be solved for the market-level fixed effect that is consistent with the actually observed number of firms in the market. The model thus predicts the total number of entrants exactly. An additional entrant would be worse off under entry than under the outside option, while all other entrants prefer being active in the market to staying out. Solving equation 3.14 for ξ^m implies:

$$\xi^m = \ln(\widehat{N}) - \ln(N^{\max} - \widehat{N}) - \ln(I^{in}(\widehat{N})) \tag{3.15}$$

The market fixed effect ξ^m imposes a level on the profit function relative to the outside option of not entering. Granting firms a choice of not entering entails several practical complications. First, the econometrician (and, possibly, active rivals) will only observe firms that actually enter a market, but not those which only consider entering. Identifying parameters of unobserved non-entry decisions is difficult. Earlier studies (Cotterill and Haller 1992) have dealt with this problem by deducing the approximate size of a potential entrant pool from the presence or absence of main competitors in different markets. This approach is not feasible here since single-outlet retailers account for a significant fraction of all stores. Instead, I investigate the robustness of the estimation results to varying the size of the potential entrant pool.

Varying the size of the potential entrant pool and consequently the fraction of firms that decide to enter the market in equilibrium provides a reflection of the market's average attractiveness to firms relative to the option of not entering. At one extreme, with an infinite potential entrant pool, the fraction of firms entering the market will be extremely small. The market's fixed effect ξ^m will then adjust relative to the outside option's fixed effect, which has been normalized to 0, to reflect the revealed low attractiveness of entering. The reverse holds in the case where every firm in the potential entrant pool decides to enter. ξ^m thus absorbs most of the effect of varying the potential entrant pool's size on location choices in the lower nest, which are based solely on expected actions undertaken by actual entrants, not by every member of the pool.

4 Data Description

4.1 Sample Markets

Geographic differentiation will only play a significant role in shaping a city's market structure if the city is sufficiently large and geographically spread out that firms can use location as a strategic instrument. The markets that were considered in earlier studies such as Bresnahan and Reiss (1991) and Mazzeo (1998) are extremely small and isolated from one another, so that differential competition by location was of no importance. On the other extreme, market definitions that have been used in other retail entry studies such as Chevalier (1995) and Cotterill and Haller's (1992) work on the supermarket industry consider the unit of observation to be an entire Metropolitan Statistical Area. With this approach, some of the intuitive appeal of considering a city or overlapping cities as a single market is lost. Video stores operating at either end of the MSA would rarely be in direct competition for customers due to the extremely high transportation cost relative to the cost of the transaction. This disadvantage applies to many convenience-driven retail industries with low transaction costs, but may not be as relevant for more expensive consumer goods such as cars or large electric appliances. Then the cost of the item may justify traveling a long distance in order to purchase it.

The cities used in this study were selected to address some of these concerns. The markets range in size between 50,000 and 150,000 people. To identify competitors operating within each market as well as potential customers who reside in the market with some accuracy, I focus on well-delimited cities or groups of cities with shared boundaries. Adjacent cities were identified by verifying which cities within 10 miles either shared boundaries with a candidate city or consisted of census tracts whose areas overlapped with both cities. An additional check was carried out by visual inspection of various candidate cities.[7] Furthermore, I excluded candidate cities if they were part of a suburban

[7] See `www.mapquest.com`.

sprawl or in a metropolitan area which makes identifying market boundaries more difficult. More formally, the sample's markets are cities or small groups of cities such that the largest city outside of the market within a distance of 10 miles has a population of less than 10,000 people and the population of the largest city within 20 miles does not exceed 25,000 people. Cities in tourist regions were excluded since the resident population accounts for only a small share of the potential customer base.

The selected markets were divided into non-overlapping cells among which firms choose their optimal location. Rather than superimposing a regular grid on each of the cities, I chose to divide the markets into cells along more natural and non-arbitrary lines. The Census Bureau breaks counties down into smaller subdivisions called census tracts. These units of on average 4,000 people were originally delineated by following neighborhood boundaries as closely as possible. While neighborhoods obviously change and shift over time, using census tracts as cells represents an attempt at dividing the sample markets into relatively coherent, internally uniform locations. Census tracts vary significantly, however, in terms of their area. Center-city neighborhoods have on average a much higher population density covering a relatively small area compared to census tracts at the outskirts of the city with more sparsely populated, larger areas. This irregularity complicates the definition of immediately adjacent locations relative to the case of a regular grid of square cells and will be addressed when estimating the model empirically.

The census tracts that overlap with the sample markets were identified using a geographic correspondence engine available from the Census Bureau. The Data Appendix describes the selection process in more detail. Since census tracts are geographic subdivisions of counties rather than of the cities themselves, the selected tracts cover an area that is somewhat larger than the area covered by the city alone. Tracts for which only a small fraction of the population lives within the city and which are more than 15 miles away from the city's center were dropped from the location choice set. Furthermore, extremely small census tracts with a population of less than 200 people were dropped as well.

The resulting set of markets consists of 151 cities drawn from most US states with a slight underrepresentation of the North East. Market size as measured by the included incorporated places' total population ranges from 53,538 to 142,303 people with an average market size of 74,367. The use of census tracts as market subdivisions leads to a slight increase of the market's final size since people who live in a tract at the outskirts of the markets, just beyond the city's official boundaries, are included in the market definition. Since residents of these tracts will, with all likelihood, consume from one of the city's video stores as well, it is sensible to include them among the market's consumers. Including surrounding residents, the average market size increases from 74,367 to 90,563. Given the selection criteria imposed upon sample markets, the population living within the markets' tracts represents a large fraction of the population residing within that general area. Thus, the consumer base for which stores in the market compete can confidently be captured by the population living in one of the market's census tracts.

Table 4.1: Descriptive Statistics, Markets and Locations (1998-'99)

	151 Sample Markets		
	Mean	Minimum	Maximum
Market level			
Population, market	74,367	53,538	142,303
Population, main city	59,428	38,495	140,494
Population, all tracts in market	90,563	51,614	183,322
Largest Incorporated Place within 10 mi.	2,618	-	9,972
Largest Incorporated Place within 20 mi.	7,916	-	24,725
Tract level			
Number of tracts	21	8	49
Tract population	4,380	247	32,468
Area (sqm)	10.10	0.1	181.50
Average distance (m) to other locations in market	3.49	1.08	8.05

Notes:
The largest incorporated place within 10 and 20 miles is relative to the centroid of the market's main city. The distance between locations within a market is computed as the distance between the tracts' population-weighted centroids.

On average, a sample market is made up of 21 tracts, ranging from markets with only eight tracts to markets with 49 tracts. Tract centers are represented by population-weighted centroids.[8] The distance between tract centers within a market averages to 3.5 miles. While the distance between a tract and its closest neighboring tract in the market is, on average, only 1.1 miles, the average maximum distance to any of the remaining tracts amounts to 8.1 miles. Given that consumers' willingness to travel a large distance for convenience shopping is small, these descriptive statistics indicate scope for geographic differentiation even in these mid-sized markets.

[8] Population-weighted centroids were obtained from the Census Bureau. They were used instead of the more standard area-weighted centroids to capture where the majority of the tract consumers lives. See the Data Appendix for more details.

4.2 Exogenous Determinants of Video Demand

Data on standard demographic characteristics of the chosen markets can generally be obtained from the Census Bureau. Data at a high level of geographic disaggregation, such as the Census Tract, is collected comprehensively in the decennial Census of Population. The last Census of Population dates back, however, to 1990. Consequently, the time gap between demographic data derived from the Census and the available firm-level data is large. As an alternative, I use 1999 data obtained from a private data vendor, Advanced Geographic Solutions (AGS), containing updated demographic estimates. The Data Appendix compares trends over time across the Census Bureau and the AGS data. Estimation of the model presented above using both data sets resulted in comparable estimates.

The demographic information was combined with data from the Department of Education on college and university locations, as well as further data from AGS covering tract-level business characteristics, such as business establishment counts and daytime working population. Comparable business summary statistics are generally not available from the Census Bureau at this level of geographic disaggregation. Tract-level demographic data was merged with firm-level data on video store locations derived from *American Business Disc 1999.* This US-wide semi-annual business directory contains information such as establishment location, chain affiliation and lines of business and is derived primarily from Yellow Page directories backed by phone inquiries. The Data Appendix contains a more detailed description of the individual data sources.

Table 4.2 provides a summary of the key variables used in the following empirical analysis. Market size indicators, i.e. tract population, have been supplemented with a set of cost shifters, such as median rent and business density. Future work will incorporate demand shifters that are specific to the case of the video retail industry, including the presence of children in the household or the proximity to colleges and universities.[9]

[9]See Hasting's Book, Music and Video, Inc. 1998 Annual Report: "The Company's primary market areas are small and medium-sized communities with populations typically ranging from 25,000 to 150,000... Key demographic criteria for Company superstores include community population, community and regional retail sales, personal and household disposable income levels, education levels, median age, and proximity of colleges or universities. Other site selection factors include current competition in the community, visibility, available parking, ease of access and other neighbor tenants..." and the Video Software Dealers' Association's (1998) *Annual Report on the Home Video Market 1998*: "The biggest demographic factor in determining a household's rental frequency ... is the presence of children. Almost three-fourths of all households with children rent at least once a month, while nearly a third rent at least once a week. Among households without children, 53% rent once a month or more and 21% rent once a week."

Table 4.2: Tract-level Demographic Characteristics and Store Location Patterns (1998-'99)

	Mean	Minimum	Maximum
Store location patterns			
Firms, market	12	3	31
Firms, tract	0.57	0	6
Firms, within 1 m of tract	1.34	0	10
Firms, within 1 - 3 m of tract	4.70	0	22
Firms, within 3 - 10 m of tract	5.72	0	28
Demographic characteristics			
Population	4,380	247	32,468
Population, within 1 m of tract	9,988	5,095	26,017
Population, 1 - 3 m of tract	34,799	16,926	79,954
Population, 3 - 10 m of tract	45,052	1,587	120,503
Median rent	378	99	1,001
Per capita income	17,470	1,680	71,053
Unemployment (%)	7.67	0	63.90
Households with children under 18 (%)	35.07	0	100
College located within tract	0.10	0	1
Business characteristics			
Establishment density per square mile	170	0	2,499

Notes:
All stores and population were placed at the tract's population-weighted centroid. Firms and population within different distance bands to the tract under consideration were computed as the sum of firms and population, respectively, in tracts for which the distance to the considered tract's centroid fell in the specified range.

As the table shows, locations within a market differ significantly from each other in terms of both the store location patterns and demographic characteristics. The observed variability in demographics will facilitate estimation of the model proposed above and will ensure the existence of an equilibrium set of location strategies resulting from the fixed point algorithm.

5 Implementation and Estimation

5.1 Adapting the Model for Empirical Estimation

When taking the model to data, slight modifications need to be made to account for the grid cell irregularity and size variability exhibited by the sample markets. I assume that all firms and consumers operating and living within a given census tract are located at the tract's population-weighted centroid. Each market is thus made up of a set of point locations, which are scattered within the city's boundaries. Cities vary furthermore in their area, in part due to differences in population, but also due to regional variations in city planning. In particular some of the sample's Mid-Western cities tend to be more spread out than their Eastern counterparts. To impose uniform distance rings around locations thus becomes more difficult than in the previous illustration based on regular square grid cells.

Distance rings were therefore modified to distance bands such that all firms located in tracts within a certain distance range from a location have identical competitive impacts upon profitability in that tract. Similarly, the own-cell competitive effect was redefined to apply to all firms located within 1 mile of the tract under consideration. This modification is of particular importance in city centers where tracts are extremely small and close to each other. In the city center, even if a given tract has only one competitor in it, that competitor would be under significantly stronger competitive pressure, being extremely close to a number of other locations, than a firm in a tract at the city's outskirts. These locations are often significantly more than 1 mile away from the next closest tract in the market.

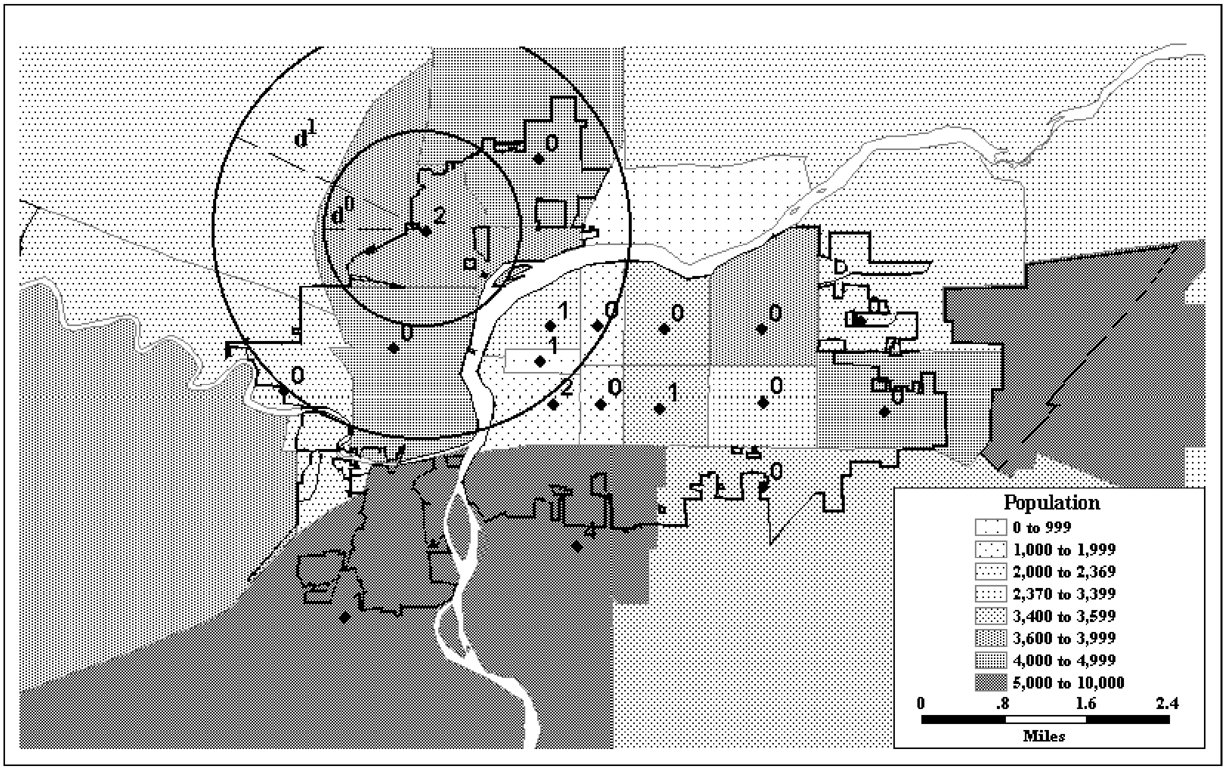
Since the spread of the city and thus the maximum distance between city tracts varies significantly as well, the band covering the most distant locations was only restricted with respect to the minimum distance that a tract had to satisfy to fall within that band. Thus, every tract in the city, independently of how distant it may be from a location at the other end of the city exerts some degree of competitive pressure. Given the documented low willingness to travel for the rental of a video,[10]this assumption appears justified if the minimum bound for that distance band is specified to be sufficiently large. The modification then simply implies that any store located within the city at a distance of more than, say, 5 miles from another store will have the same incremental impact on that store's profitability.

Figure 5.1 below shows a map of one of the smaller sample markets, Great Falls, MT, chosen for this illustration due to its regular lay-out of census tract neighborhoods. The city's boundaries overlap with 20 census tracts, not all of which are depicted in the map. The map shows clearly the variability in the tracts' areas and populations. Figure 5.1 furthermore indicates the number of competitors operating in each of the census tracts as well as distance bands around one of

[10]According to research commissioned by the Video Software Dealers' Association (1998), the average customer travels only 3.2 miles in total for a round trip to a video store.

the market's locations. The two concentric circles around the tract depict the maximum cut-off for immediately neighboring locations ($\overline{\mathbf{d}}^0$), here taken to be one mile, as well as for adjacent locations, which are between $\overline{\mathbf{d}}^0$ and $\overline{\mathbf{d}}^1$ miles away from the location.

Figure 5.1: Sample Market - Great Falls, MT



The profit function is imposed on each of the sample markets' locations. Using predetermined cut-off values to characterize the distance bands, the great circle distance[11] between all location pairs in a market is computed to determine the set of immediately neighboring tracts, adjacent tracts, and more distant tracts for each location.

[11] To account for the curvature of the Earth, the great circle distance is computed as the length of the shortest arc on the surface of a sphere connecting the two locations. The great circle distance thus assumes away differences in elevation and abstracts from the slightly elliptical shape of the Earth. It is, however, highly exact for small distances. Even the distance between antipodal points is computed with an approximation error of only about 1 mile for an actual distance near 12,000 miles. It does not, however, reflect driving distances along existing roads.

5.2 Estimation Strategy

For a given parameter vector $(\boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\rho}, \boldsymbol{\sigma}, \boldsymbol{\mu})$, the system of equations defined by equation 3.10 is solved numerically for its fixed point in probability space, for each city in the market. The number of tracts that make up the sample markets varies greatly. The dimensionality of the system of equations varies accordingly, being one less than the total number of market locations due to the constraint that the probabilities sum to one. At the lower nest, the nested fixed point algorithm over market m's $(L^m - 1)$ locations results in a vector of structural location choice probabilities, $\widehat{\mathbf{p}}^m$. These predictions are then stacked across markets to yield a vector of predicted location choices across markets. While adding extra markets to the data set improves the robustness of the results, it also increases the computational burden by adding on a further set of equations for which the fixed point algorithm has to be solved. The optimal parameter values, $(\boldsymbol{\beta}^*, \boldsymbol{\theta}^*, \boldsymbol{\rho}^*, \boldsymbol{\sigma}^*, \boldsymbol{\mu}^*)$ are found by nesting the fixed point algorithm into a maximum likelihood routine. Using a multinomial likelihood function, the predicted firm distribution over locations $\widehat{\mathbf{p}}^m$ is matched to the actually observed firm location pattern, described by the share of firms located in each of the cells, $s_i^m = \frac{n_i^m}{\widehat{N}^m}$.

The second component of the likelihood can be attributed to the market-level measurement error ξ^m, which is assumed to be normally distributed with mean μ and variance σ. The full log-likelihood function applied to this problem is given by:

$$\ln L = \sum_{m=1}^{M} N^m \sum_{i=1}^{L^m} s_i^m \ln(\widehat{p}_i^m) - \frac{M}{2}[\ln(2\pi) + \ln(\sigma^2)] - \frac{1}{2\sigma^2} \sum_{m=1}^{M} (\xi^m - \mu)^2 \tag{5.1}$$

Some caveats are in order. First, the current estimation routine treats each of the errors identically, abstracting from any within-market correlation. Relaxing this feature can be more easily accomplished by specifying an appropriate weight matrix for a generalized methods of moments estimator, which directly matches predicted shares to observed shares. Second, the Logit functional form assumption results in strictly positive, even though possibly minute, probabilities for all possible location choices, and non-integer predictions for the numbers of entrants are the norm. Thus, the model predicts that each location will be chosen by at least a fraction of a firm, and zero shares, equivalent to a location not being chosen by any firm, cannot be predicted. One way to interpret this fractional firm is to think of it as a store that primarily carries other merchandise and for whom video retail only makes up a small share of its business. These kinds of stores are likely not to be included in my dataset consisting of stores for which video retailing is one of their two primary lines of business.

5.3 Baseline results under varying potential entrant pool sizes

Table 5.1 depicts estimation results for the nested Logit model using two alternative measures for the potential entrant pool. The parameter estimates depicted in table 5.1 were obtained by maximizing equation 5.1 with respect to the vector of underlying parameters using a Nelder-Meade optimization algorithm. Starting values for this optimization were obtained by performing a grid search over the parameter space.

On the demand side, the estimation incorporates primarily market size characteristics in the form of own tract and surrounding populations. On the cost side, tract-level median rent captures some of the immediate costs of running a retail establishment in that location. Part of the attractiveness of a retail location stems from the easy accessibility and convenience that the location offers to shoppers. While I do not have information on whether a store is located along a major commuting road or whether it is part of a strip mall receiving spill-over business from other stores in the mall, a tract's commercial character is proxied by its business density. The use of a tract's business density as a catch-all proxy for the general business character of the location also picks up whether a tract is purely residential, possibly governed by zoning laws ruling out the establishment of commercial enterprises.

Rivals are allowed to influence profits according to three intensity levels. Immediate competitors include all firms located within one mile from each other. Neighboring competitors are firms located between 1 and 3 miles from each other, while remaining competitors capture every other firm active in the market. Experimenting with the cutoff between the neighboring and remaining categories had only small quantitative effects on the results. Table 7.2 in the appendix lists the explanatory variables in further detail.

The mean value of not entering was set to 0 for each of the markets, providing a normalization for each of the markets' underlying profitability levels. The location choice model from equation 3.10 was estimated using two different assumptions about the potential entrant pool, one arbitrarily fixing $N^{\max}$ to 50 for each of the markets, the second setting $N^{\max}$ to twice the actually observed number of entrants. The nested Logit estimation results prove robust to changing the size of the potential entrant pool, its impact being absorbed by the estimate of the mean of the market-level fixed effect, μ. The remaining parameter estimates are in general statistically significant at traditional levels and of the anticipated sign. Population exerts a strongly positive push, decreasing

Table 5.1: Parameter Estimates, Location Choice Model

Variable	Potential Entrant Pool = 2 x total entrants, Coefficient (std. error)	Potential Entrant Pool = 50 firms, Coefficient (std. error)
	(1)	(2)
Population, chosen location	**1.6658**	**1.5768**
	(0.3196)	(0.3039)
Population, between 1 and 3m of chosen location	**1.0525**	**1.0809**
	(0.1146)	(0.1296)
Remaining population in market, more than 3m of distance from chosen location	**0.6726**	**0.7174**
	(0.1705)	(0.1820)
Median rent, tract-level	**-0.2276**	**-0.2093**
	(0.2934)	(0.3112)
Business density, tract-level	**0.3055**	**0.4915**
	(0.1374)	(0.2382)
Competitive effect, immediate competitors (located within 1m of distance)	**-1.7096**	**-1.6919**
	(0.3653)	(0.3859)
Competitive effect, neighboring competitors (located between 1 and 3m of distance)	**-1.0328**	**-1.0562**
	(0.0936)	(0.1150)
Competitive effect, remaining competitors (located at more than 3m of distance)	**-0.7205**	**-0.7370**
	(0.1001)	(0.1121)
ρ	**1.0898**	**1.0973**
	(0.4702)	(0.5190)
μ	**0.7606**	**-0.1852**
	(0.3243)	(0.3723)
σ	**3.2007**	**3.6487**
	(0.9189)	(1.0466)
Log-likelihood	-5899.53	-5923.08

Notes:

Results based on 1999 demographic and firm data.

with distance. Neighboring as well as distant rivals push down profits. However, the competitive pressure exerted by neighboring rivals decreases significantly relative to the impact of immediate competitors, and drops even further for distant competitors. Thus, incentives for firms to differentiate are large: spatial separation can be effectively used to shield one's profit from a large number of the rivals operating in the same market.

5.4 Entry and Location Predictions: Illustration of Results

The empirical patterns of location choices observed in the data show clustering of firms as well as spreading into less attractive locations. In general, population density declines as one moves from the center city to the city's outskirts. This trend is in general not mirrored by store density. In particular, as firms spread out in area, the effect of competitors on profits changes, making some of the peripheral locations more attractive choices despite a reduced access to customers. A model of location choice that does not incorporate the effect of competitors' actions on firm profits may thus lead to excessive clustering in highly populated areas.

Figure 5.2 illustrates the model's ability to predict such location patterns relative to a model based on demographics only. The figure depicts the Census tracts making up the Wilmington, NC market. The first two panels show the Census tracts' population patterns and the corresponding firm distribution. We observe some clustering of firms in the two Northern tracts at the outskirts of the city, reflecting these locations' advantages of being shielded from competitors. At the same time, clustering in the city center occurs in locations that have easy access to a large share of the market's overall population. Figure 5.2's lower panels depict the prediction errors, computed as the difference between the actual and predicted share of firms in the location, associated with the estimated parameters depicted in table 5.1 on the left and with estimated parameters for a simplified model based on demographic characteristics only, setting $\theta_0 = \theta_1 = \theta_2 = 0$.[12] The maps show that the full model with competitive effects explains clustering in the Northern and Southern locations better. Nevertheless, the full model does not predict the location choices in the central area very well, pointing to other demographics besides the cells' populations that determine these locations' relative attractiveness.

[12] Note that this is equivalent to setting $\theta_0 = \theta_1 = \theta_2 = \theta$, a constant, resulting in identical competitive impacts across locations.

Figure 5.2: Location Choices - Wilmington, NC

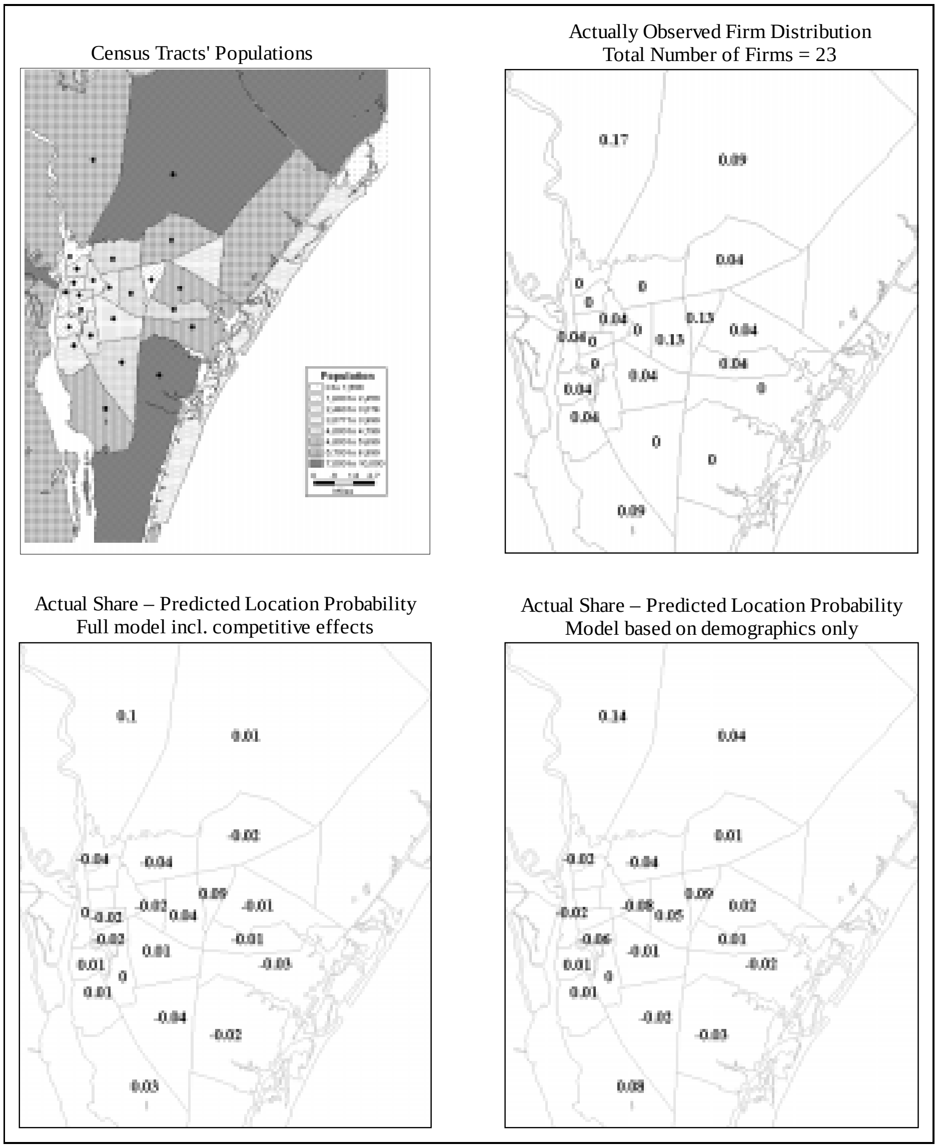
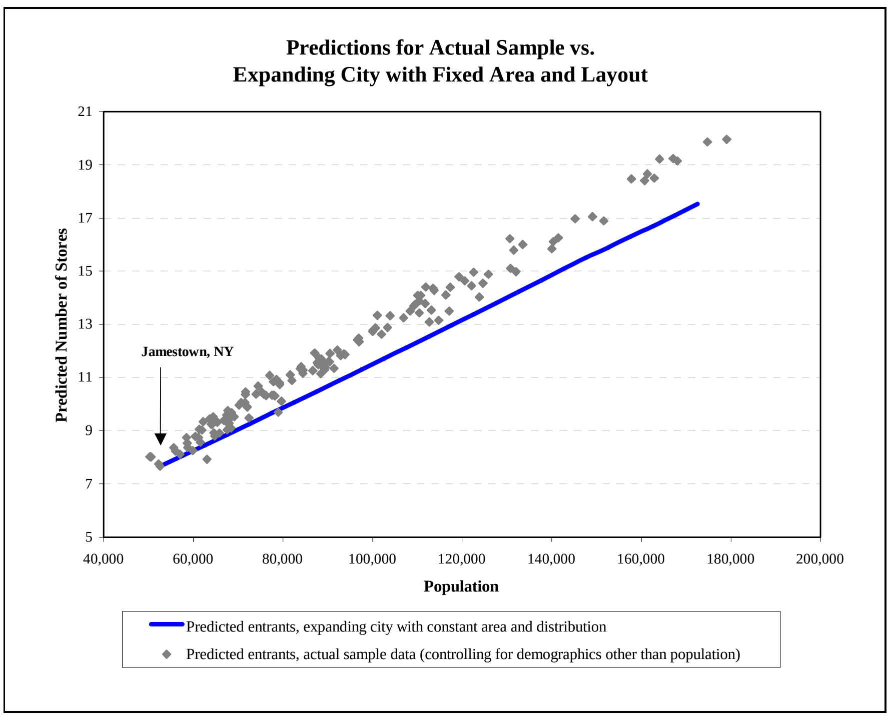


Figure 5.3 illustrates the role of increasing spatial dispersion on expected entry patterns as cities grow in population. To do so, the figure compares the expected number of entrants for the sample markets, which grow both in terms of size and area, with an alternative growth path of a city that grows in population only. Starting with one of the smallest sample cities, Jamestown, NY, with 12 locations, I increase Jamestown's population incrementally in intervals of 5,000 people. The growth process leaves the number of locations, their lay-out, and the relative population shares across locations unchanged. To abstract from cross-market and cross-location variations in rent

and business density that could drive entry patterns, I set the corresponding parameters to zero. The figure thus contrasts the scenario, in which cities grow naturally in population, area, and the number of locations, to one in which the city grows vertically only, leaving its area and cell lay-out unchanged. It demonstrates the effect of increasing markets' geographic space as cities expand on firms' ability to capture localized market power by spatial differentiation. The solid line represents the growth path of expected entrants into the expanding Jamestown market. It lies significantly below the scatter plot of expected entrants into the sample markets. By the time Jamestown has grown in population to 150,000, this difference amounts to an increase in the expected number of entrants of approximately 15 %.

Figure 5.3: The Role of Spatial Dispersion in Entry



5.5 Comparison with Model of Entry without Product Differentiation

The results presented in table 5.1 strongly support the hypothesis that firms choose to differentiate spatially in order to weaken competitive interaction. This suggests that predictions of the number of entrants into a market may be significantly biased when ignoring this dimension of product differentiation in firms' decision making. Allowing for entrants of different product types, here at different locations, would imply that, even in markets with a large number of competitors, industry conduct is far from being perfectly competitive, despite the fact that models with identical types may suggest the converse.

To compare the model's implications for the equilibrium number of competitors to those based on a model without types, I estimate a standard, perfect information, ordered Probit model relating the number of entrants to the size of the market, measured by population. Following the set-up used in Bresnahan and Reiss (1991), a representative firm in market m when there are N total firms or $N-1$ competitors earns profits of the form:

$$\Pi_N^m = S^m V_N(\alpha) - F(W^m, \gamma) + \varepsilon^m \tag{5.2}$$

$V_N(\alpha)$ denotes variable profits earned by one of the N competitors from serving a representative consumer, which can be multiplied by total market size, S^m, to yield total variable profits. Reducing total variable profits by fixed costs, $F(W^m, \gamma)$, results in total observable profits, $\overline{\Pi}_N^m$. ε^m represents unobservable components of the profit function that are identical for each firm and are assumed to come from a standard normal distribution. To be comparable to the results from the product type model, the profit function is parameterized as follows:

$$\begin{aligned}\Pi_N^m &= Pop^m(\alpha_1 + \sum_{n=2}^{N} \alpha_n) + (\gamma_0 + \gamma_1 Medrent^m + \gamma_2 Busdens^m) + \varepsilon^m \\ &= \overline{\Pi}_N^m + \varepsilon^m\end{aligned} \tag{5.3}$$

where Pop^m represents the market's total population, obtained from summing across the population of all census tracts in the market, $Medrent^m$ denotes population-weighted average median rent, and $Busdens^m$ was computed as the sum of establishments across the market's census tracts divided by the sum of the census tracts' areas. The competitive impact of additional firms is treated as accumulating dummies. Each additional firm, n, adds an incremental competitive effect, α_n that we expect to be negative. To identify the parameters of the model, an equilibrium assumption is imposed: if we observe n active firms in a given market, these n firms need to make non-negative profits, while $n+1$ firms would make negative profits. Econometric identification results from cross-market variation in the observed number of competitors.[13] The distributional assumption on

[13] For a more detailed description of the properties and derivation of the ordered Probit model, see Bresnahan and Reiss (1991), pp. 988-992.

ε^m implies that

$$
\begin{array}{lll}
\Pr(0 \text{ firms enter}) & = \Pr(\overline{\Pi}_1^m < 0) & = 1 - \Phi(\overline{\Pi}_1^m) \\
\Pr(1 \text{ firm enters}) & = \Pr(\overline{\Pi}_1^m \geq 0 \text{ and } \overline{\Pi}_2^m < 0) & = \Phi(\overline{\Pi}_1^m) - \Phi(\overline{\Pi}_2^m) \\
\ldots & & \\
\Pr(\text{more than } N \text{ firms enter}) & = \Pr(\overline{\Pi}_N^m \geq 0) & = \Phi(\overline{\Pi}_N^m)
\end{array}
\tag{5.4}
$$

where Φ denotes the standard normal cumulative distribution function. The competitive impacts, α, can only be identified for size categories that are sufficiently represented in the data. Since very few sample markets have less than 5 active competitors, these are combined into one category with $n \leq 5$. Furthermore, I assume that additional entrants beyond the 19th firm do not depress profits any further, resulting in a total of 15 categories. The ordered Probit likelihood was adjusted accordingly:

$$
\begin{aligned}
\log L \quad = \quad & \sum_{m=1}^{151} \mathbf{1}(n^m \leq 5) \log(1 - \Phi(\overline{\Pi}_j^6)) + \sum_{m=1}^{151} \sum_{j=6}^{18} \mathbf{1}(n^m = j) \log(\Phi(\overline{\Pi}_j^m) - \Phi(\overline{\Pi}_{j+1}^m)) + \\
& \sum_{m=1}^{151} \mathbf{1}(n^m \geq 19) \log(\Phi(\overline{\Pi}_j^{19}))
\end{aligned}
\tag{5.5}
$$

Table 5.2 displays the results of the ordered Probit estimation based on the sample of cities used in the previous section. The demographic parameters are significant and have the anticipated signs. The competitive impacts are consistently negative, driving down profits significantly as more firms enter.

The estimated parameters for the models with and without product differentiation can be used to investigate the contributions of product differentiation to the expected number of competitors supported by a given market. The importance of product differentiation in this context is likely to be a function of city-specific characteristics: how population is distributed across locations or how the relative attractiveness of locations varies by rent or business climate. To look at markets of more extreme demographic distributions than found in the actual data, I generate a set of simulated demographic data for 150 cities with 25 locations arranged according to a 5 by 5 regular grid. Predictions based on the simulated data set that contains more diverse as well as more similar cities than those observed in the sample data provide better insights into when cell demographics are distributed such that differentiated competition between firms pays off most.

Given demographic and cost information for an alternative set of cities, the parameter estimates shown in tables 5.1 and 5.2 can be used to compute the underlying, unobserved profitability at

Table 5.2: Parameter Estimates, Perfect Information
Ordered Probit Model

	Coefficient	Std. Error	Firms in Category	
Population	0.588159	0.07851		
Median rent	−0.001117	0.22620		
Business density	0.052336	0.13860		
γ_0	−2.47155	0.08369		
α_2	−1.06497	0.07852	$n = 6$	3
α_3	−0.17254	0.06498	$n = 7$	7
α_4	−0.37249	0.07374	$n = 8$	18
α_5	−0.71260	0.07862	$n = 9$	16
α_6	−0.45914	0.07220	$n = 10$	9
α_7	−0.21448	0.05970	$n = 11$	10
α_8	−0.22857	0.06183	$n = 12$	18
α_9	−0.42017	0.07812	$n = 13$	11
α_{10}	−0.27264	0.06948	$n = 14$	5
α_{11}	−0.12055	0.05008	$n = 15$	6
α_{12}	−0.16138	0.05894	$n = 16$	8
α_{13}	−0.22405	0.07259	$n = 17$	7
α_{14}	−0.19845	0.06822	$n = 18$	6
α_{15}	−0.20524	0.07837	$n \geq 19$	15
Log-likelihood	−367.0066			

Notes:
Results based on 1999 demographic and firm data.

the city-level and for specific disaggregated locations. For the asymmetric information model, the parameter estimates for the case of a 50-firm potential entrant pool were employed. The expected number of entrants predicted by the models can be derived by integrating over the unobservable components of the respective profit functions. In the case of the ordered Probit model with additive, standard normal disturbances, this reduces simply to finding the number of firms, $\overline{n}$, for which $\Pi(\widehat{\alpha}, \widehat{\gamma})_n \geq 0$ and $\Pi(\widehat{\alpha}, \widehat{\gamma})_{n+1} < 0$.

In the case of the asymmetric information model with spatial differentiation, Gaussian quadrature methods are used to integrate over the unobservable market-level fixed effect, ξ^m, given its empirical distribution $N(\widehat{\mu}, \widehat{\sigma}^2)$. Each of the ξ^m draws is consistent with a predicted number of entrants $\widehat{n}$, which satisfies the equilibrium entry condition outlined in equation 3.14. To determine the equilibrium number of active rivals, the market-level probability of entry is added to the system of location choice equations. This expanded system of equations is then solved numerically for the equilibrium location conjectures, $\widehat{\mathbf{p}}^m$, and equilibrium entrants, $\widehat{n}^m$. Using quadrature nodes as values for ξ^m, the expected number of entrants into a city, $\overline{n}$, can be computed as a weighted average of entrants consistent with the various ξ^m values.

I compute entry predictions for an appropriately constructed set of hypothetical cities with simulated demographic data. For a given location, location centroids are spaced at a distance of 1.375 miles. This results in an average distance between grid cells of 3.64 miles, closely reflecting the average distance between census tracts observed in the actual data. Data for each of the locations' demand and cost shifters, population, median rent, and business density, are drawn from log-normal distributions. Within a series, draws are spatially correlated for all cells at a distance of at most 3 miles. The underlying normal distribution's mean and covariance structure is adjusted to yield log-normal draws whose descriptive statistics closely mirror the actual data's properties. The simulated cities are thus representative of the mid-sized markets on which the previous analysis is based. Table 5.3 contrasts the simulated and actual samples' properties.

Table 5.3: Comparison of Cell-level Demographic Characteristics, Actual versus Simulated Data Sets

	Actual Data		Simulated Data	
	Mean	Within-market std. dev.	Mean	Within-market std. dev.
Locations' Demographics				
Population	4,380.38	2,091.06	4,559.76	2,025.40
Median rent	380.97	84.31	359.26	90.48
Business density	169.79	250.16	163.61	234.75
Average distance to remaining cells (m)	3.49		3.64	

Notes:
Simulated cell populations were placed at the grid cell's centroid, assuming a uniformly distributed population across the grid. Columns (3) and (5) depict the average, city-level standard deviation in the locations' demographic variables.

Figure 5.4 graphically compares the two models' predictions for the expected number of entrants consistent with the estimated parameter values and the simulated data. Market population is found to be strongly positively correlated with predicted entry for both models. As figure 5.5 shows, however, the model with types predicts a larger number of entrants than the standard model without types for 89% of the cities. On average, the spatially differentiated model predicts entry of 20.21% more firms relative to the alternative model.

Table 5.4: Descriptive statistics, Predicted Number of Entrants

	Predicted Number of Entrants	
	Model with Identical Firms	Spatial Competition Model
Minimum	8	11.77
Mean	12.34	14.56
Maximum	15	18.06

Notes:
Results based on simulated cell-level data for 150 hypothetical cities. To compute predictions for model without product differentiation, data was aggregated to the city-level.

The model with product types allows demand to vary with customers' distance to the location. Similarly, cost factors vary by location. Consequently, there are some extreme cases in which the model without product differentiation overpredicts entry. Figure 5.6 shows an example of such a city. This simulated city is characterized by widely varying business densities across locations. In particular, the city's business density exhibits an extreme spike in one of the corner locations, exceeding the average business density of the remaining locations by a factor of 30. While this cell is a superior location choice, the spatially differentiated model recognizes that the remaining cells are significantly less attractive for firms. Abstracting from differences among locations leads in this case to an overstatement of the city's average attractiveness such that more competitors choose to operate in the city in equilibrium in the market-level model without differentiation.

In most cases, however, the distribution of demographic characteristics is less extremely skewed. In sample cities where the demographic distribution among cells is relatively flat, the introduction of spatial differentiation does not have a significant impact on the predicted equilibrium number of entrants. Figure 5.7 depicts a simulated city with much more evenly distributed demographic characteristics. Cell population ranges from a minimum population of $1,500$ to a maximum of $7,000$ and there is no significant spatial clustering. Relative to the previous example, businesses are more evenly distributed across the city, with several, geographically spread-out spikes.

Lastly, figure 5.8 shows a simulated market that most closely resembles a typical real-world city. The market exhibits a large concentration of population in its center. Population drops off towards the city's edges where the business climate is more attractive and business density is high. In such an environment, the demographic distribution significantly alters market attractiveness for a larger number of firms. Both locations at the center, where most of the population is easily accessible, as well as at the edge, where the business climate is superior and firms are shielded from their competitors, support a significant share of firms. Thus in total this market supports a larger number of competitors than a model based on average demographic characteristics and uniform competitive interaction among firms may suggest.

Figure 5.4: Comparison of Predicted Number of Entrants under Alternative Models

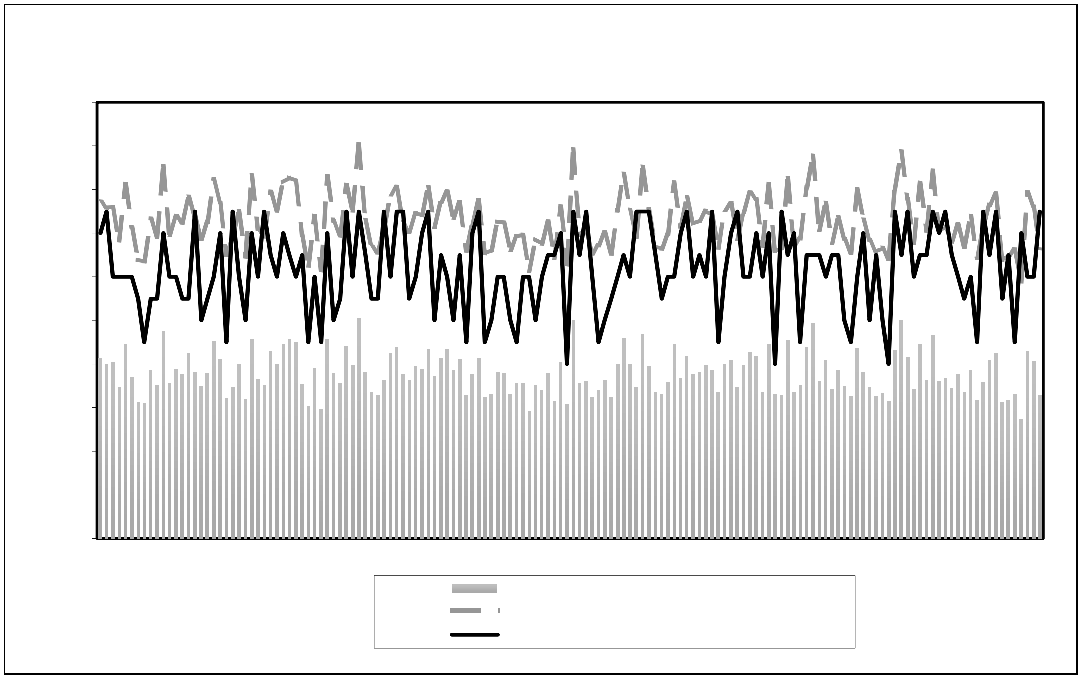


Figure 5.5: Distribution of Differences in Predicted Number of Entrants, Alternative Models

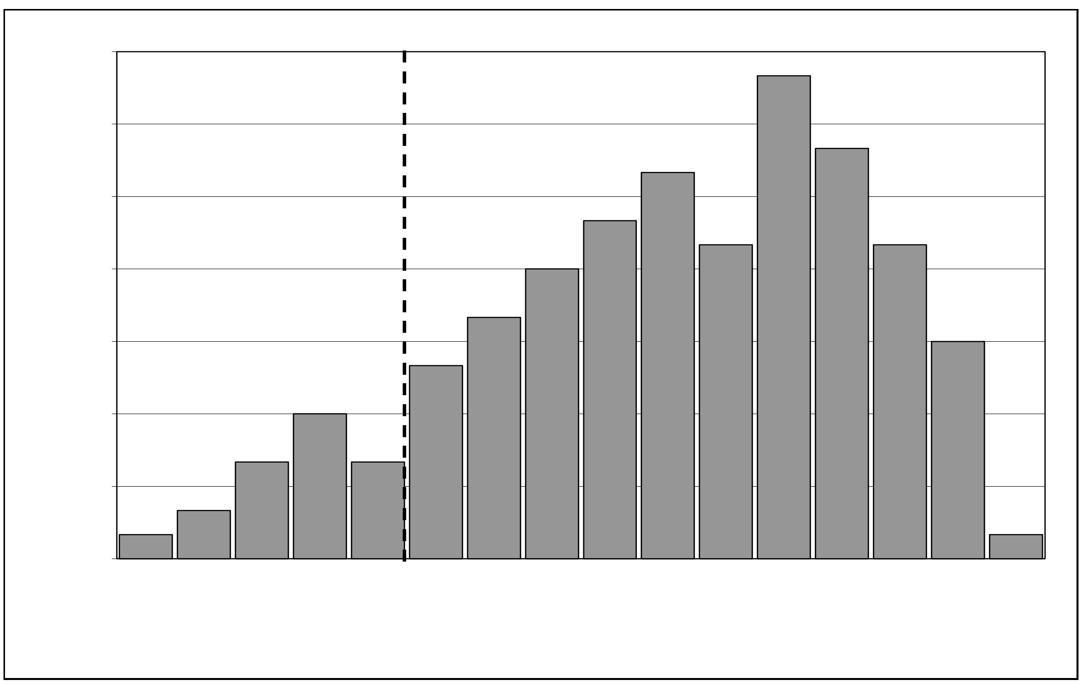


Figure 5.6: Sample City 1 − Model without Differentiation Predicts More Entry

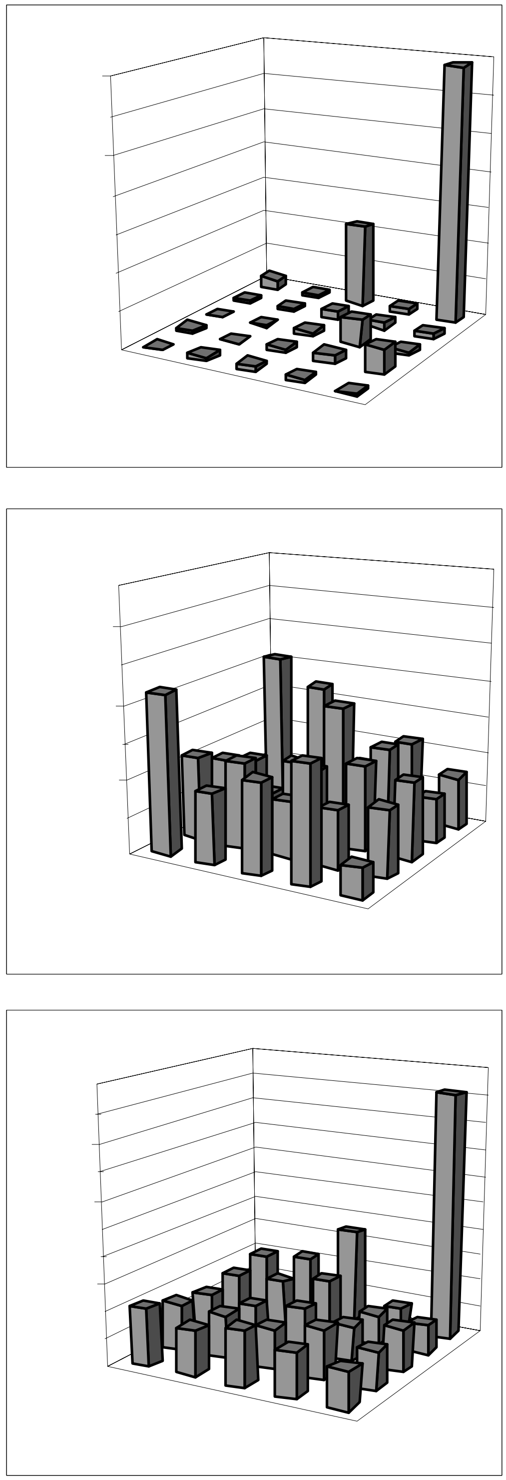


Figure 5.7: Sample City 2 − Models with and without Differentiation Predict Similar Numbers of Entrants

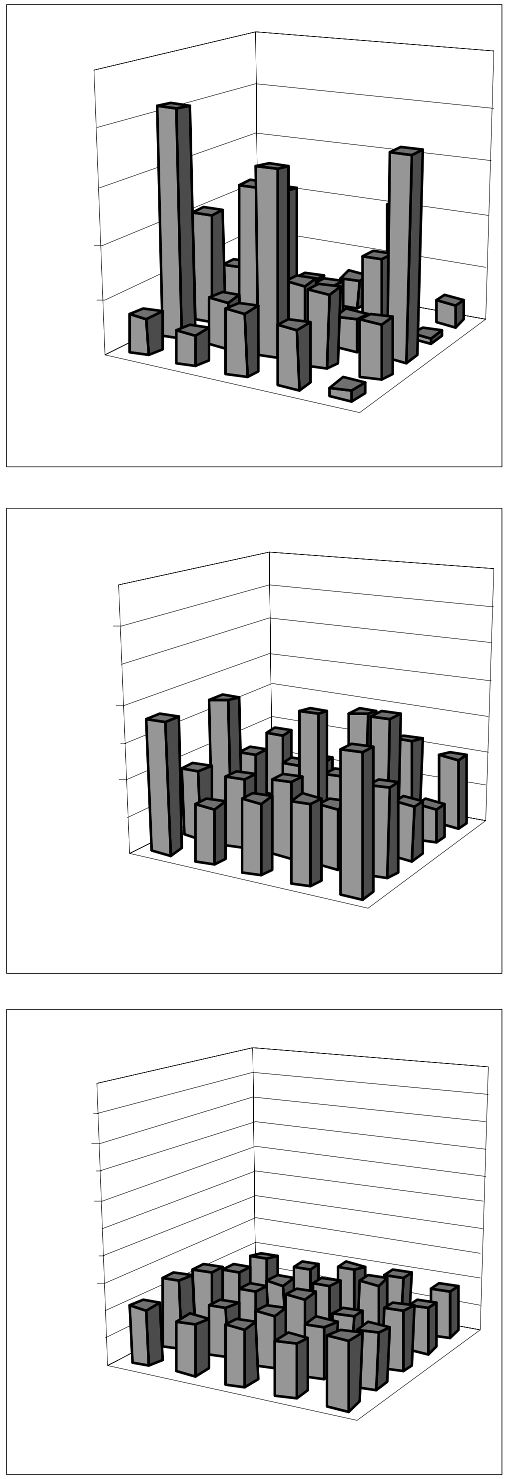
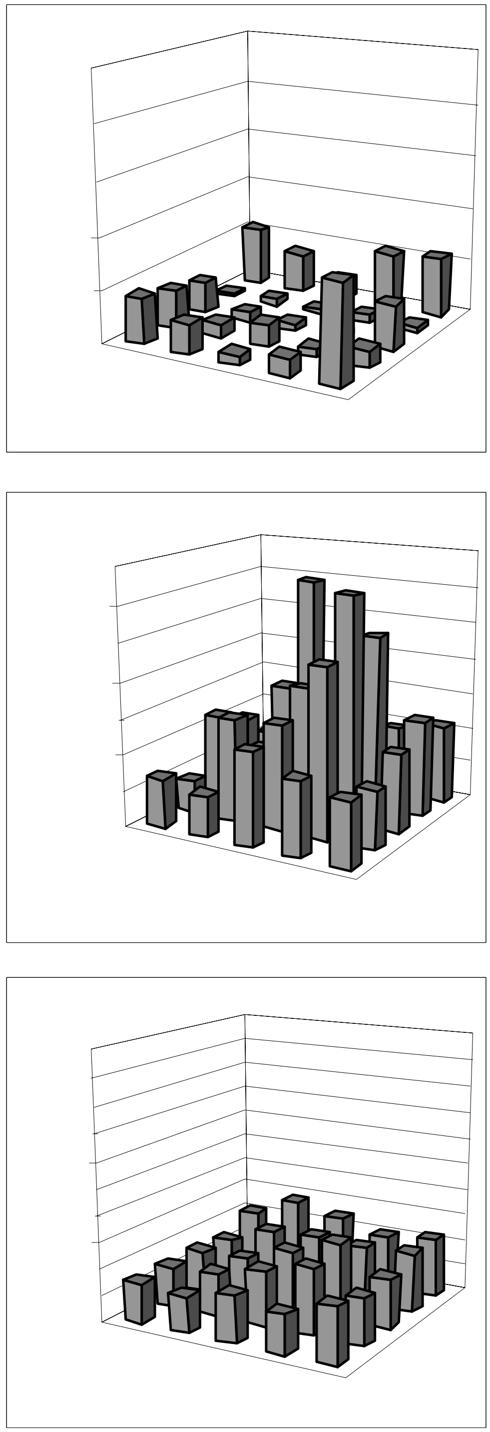


Figure 5.8: Sample City 3 − Model without Differentiation Predicts Significantly Less Entry



6 Conclusions and Extensions

This paper has presented a framework for incorporating endogenous product-type choices into firms' entry decisions and has measured the subsequent impact on market structure. Firm interaction is modeled as a static game of imperfect information where firms do not have complete knowledge of the types of rivals they will be competing with in equilibrium. Entry and subsequent product-type choice thus involve a degree of uncertainty regarding the intensity of post-entry competition and consequently profits. Ex-post regret is feasible should a firm decide to enter into what turns out to be an unprofitable location. This framework can capture situations in which firm characteristics that are largely unobservable by rivals contribute significantly to firm profitability. In the current application, which looks at location choices in the video retail industry, one such characteristic may be firms' intangible assets in the form of managerial talent. Examples from other contexts are easy to come by, however. For R&D intensive industries, a significant determinant of a firm's success is its intellectual property, which provides a competitive edge. Firms will often go to great lengths to keep the results of their R&D efforts secret. Other examples may include activities in which creativity and innovativeness allow firms to carve out distinct niches for themselves, such as design or advertising.

The incomplete information set-up comes with several distinct advantages over a complete information model of entry and product-type choices. In particular, it yields easily solvable equilibrium conjectures and location choice probabilities, which are found to be unique provided that there is sufficient variation in observable demand and cost shifters across product-types. Furthermore, the Bayesian equilibrium concept significantly facilitates applying the model to a realistic, large-dimensional product-type choice set as it does not require verification of a large number of profit constraints.

As an illustration, the model is applied to spatial product-type choices using data from the US video retail industry. The results indicate not only that firm profitability and market structure are endogenously determined, but also that firms have very strong incentives to differentiate themselves from their competitors and that rivalry between firms significantly decreases with the distance between competitors. Simulations and city-growth experiments underline the importance of incorporating product-type choices into the entry process. Relative to a complete-information model without product or firm types, the model with spatial differentiation predicts, on average, an increase in the expected number of entrants into a market of 20.21%. Furthermore, firms' abilities to capture localized market power by spatial differentiation increase in the size of the product space, allowing for more entry under a larger product space.

In extensions to this paper, I hope to improve upon the above data treatment and methodology in a number of ways. First, a more careful incorporation of factors which shift retail and, more specifically, video-retail demand will be necessary. The current analysis uses only population-based variables to characterize total market demand. Other factors, which will provide a more complete picture of demand, include population characteristics, such as the presence of children or proximity to a college.

On the methodological side, I plan to incorporate firms' expectations over their rivals' entry decisions into the model. At present, firms form expectations only over the location decisions of those rivals that actually enter the market. The entry decision by all members of the potential entrant pool is, for now, only incorporated in the econometrician's treatment of the entry choice. To integrate the entry decision into firms' expectations, their conjectures over their rivals' behavior will be expanded to include the choice of remaining inactive. In this way, firms' location decisions will reflect the likelihood that each of its potential competitors will decide to enter, as well as where they would locate. The model will then yield a full set of equilibrium beliefs for every possible location choice, including the option of staying outside of the market. Incorporating the expected outcome of their rivals' entry choices into firms' decision making will permit an evaluation of the implications of product differentiation for predicted firm conduct, such as the number of firms supported by a market.

The model presented in this paper differs from other models put forth in the literature in two important aspects: first, it incorporates firms' product-type choices and second, it introduces firm-types. Out-of-sample predictions of this model cannot separate the joint effect of product differentiation and incomplete information of rivals' types in determining entry. The disentangling of these two effects would however be possible using a model such as the one outlined in the previous paragraph, which yields direct predictions for the number of entrants into a market. By imposing restrictions on the relevant demand and competitive parameters, alternative predictions for the number of entrants could then be derived for a model without product differentiation, but with asymmetric information. The out-of-sample experiments conducted in this paper may be used to contrast predictions between models with and without asymmetric information, as well as with and without product differentiation.

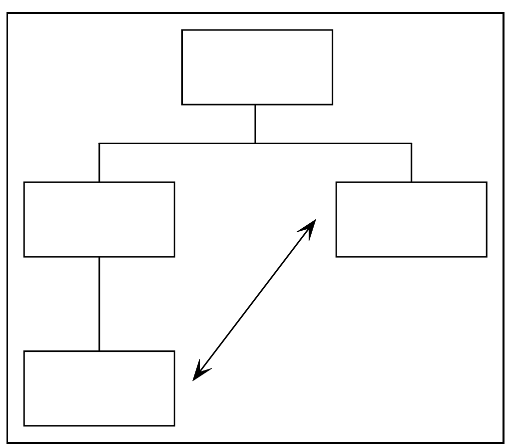
Lastly, the model can be extended to allow for systematic differences among firms, along, for example, a chain-affiliation dimension. One approach, which appears computationally feasible, would allow firms to choose whether to enter a given location as either a chain or a non-chain store and to allow the competitive impacts of these two kinds of firms to differ.

7 Appendix

7.1 Data Sources and Construction of Data Set

The geographic unit of observation is the census tract, a small geographic entity with an average population of 4,000 people that, at delineation, roughly corresponded to a neighborhood. Each of the US counties is divided into non-overlapping census tracts. The census tract is therefore not a subdivision of a city or place, which can, in principle, cross county borders (see Figure 7.1 for a schematic overview of Census Geography). To determine which census tracts share area and population with a given city, I used a geographic correspondence engine, *MABLE/Geocorr* Version 2.5, available on the Census Bureau's web site.[14] This program provides, among others, a mapping utility from the level of the census tract to the level of incorporated places to result in a comprehensive list of census tracts whose area overlaps with each of the incorporated places. In addition, the utility gives the percentage of the tract's population residing within the city and the percentage of the city's population residing within the tract. These data enabled me to choose the tracts which make up each of the cities in my sample. Since the census tract is not a subdivision of a city, I naturally included the city's immediately surrounding population that resides in a tract at the edge of the city, but not within the city's official boundaries.

Figure 7.1: Overview of Census Geography



As a side product, *MABLE/Geocorr* also produces population-weighted centroids, which I used as location centers instead of the standard area-weighted centroids. Population-weighted centroids

[14] *MABLE/Geocorr* can be accessed at `http://www.census.gov/plue/`

more accurately represent where the majority of tract consumers resides. For locations at the edge of a city, tracts' areas tend to be fairly large with the associated drop in population density at the city's outskirts. The area-weighted centroid would therefore significantly overstate the attractiveness of these tracts with respect to isolation from competition since their centroids would be quite a distance from the other locations in the city.

The demographic make-up of the sample cities and their corresponding census tracts is based mainly on data from the 1990 Census of Population and 1999 data from Advanced Geographic Solutions, Inc. Table 7.1 shows trends in the two databases over the nine year time period. Tract-level demographic data was used to characterize tracts in terms of population, per capita income, and the percentage of households with children. Furthermore, Census information on the total number of persons residing in college dormitories within each tract was combined with information from the Department of Education's *IPEDS* College and University data base[15] to create a dummy variable indicating whether a college or other institution of higher education is located within the census tract. The demographic information was supplemented with data provided by Advanced Geographic Solutions, Inc. on tract-level firm counts, average establishment size and daytime working population.

Table 7.1: Comparison of 1990 Census of Population data and 1999 AGS data

	Mean	Minimum	Maximum
Population, sum of all tracts in market			
1990 Census of Population	84,520	55,800	168,606
1999 AGS Database	90,563	51,614	183,322
Tract Population			
1990 Census of Population	4,000	256	37,612
1999 AGS Database	4,380	247	32,468
Tract Per Capita Income			
1990 Census of Population	11,960	1,320	41,140
1999 AGS Database	17,470	1,680	71,053

1998 firm-level information concerning store location, chain affiliation and lines of business has been taken from *American Business Disc 1999*. The information derived from the database was checked for reliability by comparing the location pattern observed for the large, public video chains to information contained in the respective firms' public SEC filings. For all of the six public chains

[15]The database is available at `http://nces.ed.gov/ipeds/cool/`

(Blockbuster Video, Hasting's Book, Video and Music, Hollywood Entertainment, Movie Gallery, Video Update, and West Coast Entertainment), the database contained more than 95% of the chains' outlets as per their 1998 fiscal year 10-k annual report. It is more difficult to verify the database's completeness with respect to smaller chains and single outlet stores. Nevertheless, the total number of listed establishments engaging in video rental amounts to 33,964 stores. This closely matches industry analyst estimates of the industry's size ranging from 30,000 to 35,000 outlets.[16] To match up store locations with census tracts, each store's address was initially geocoded by assigning it a longitude and latitude using the *GIS* software *Maptitude.* The resulting geographic location was then assigned to the corresponding census tract.

Distances between locations were computed based on the Haversine formula for determining the great circle distance on a sphere using an approximate earth radius of 3,956 miles (Sinnott 1984). The distance between two points with geocodes $(lat_1, lon_1)$and (lat_2, lon_2) is thus given by:

$$d_{12} = 2R \arcsin \left[\min \left\{ ((\sin(0.5(lat_2 - lat_1)))^2 + \cos(lat_1)\cos(lat_2)(\sin(0.5(lon_2 - lon_1)))^2)^{0.5}, 1 \right\} \right]$$

where R denotes the radius of the Earth.

[16]See Advanstar Communications (1998), and Video Software Dealers' Association (1998).

7.2 Variable description for results in Section 5

Table 7.2: Definition of Variables used in Estimation

Variable	Definition
Population	Total number of persons residing in tract (0000)
Per Capita Income	Average per capita income (0000)
% of Population aged less than 18	Percent of population of age 17 and below out of total population
Median Rent	Median gross rent for renter-occupied housing units ($000)
Business Density	Establishments per square mile (0000)
Population, between 1 and 3 mi. of chosen location	Sum of population of tracts located between 1 and 3 mi. of cell, (0000) (distance is calculated between tracts' population-weighted centroids)
Remaining population in market, more than 3 mi. chosen location	Sum of population of tracts that are more than 3 mi. in distance from cell, covering all remaining tracts whose area overlaps with the city (0000)

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