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Disciplines

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February 23, 2004

Abstract

This paper presents a model of entry with endogenous product-type choices. These choices are formalized as the outcomes of a game of incomplete information in which rivals' differentiated products have non-uniform competitive effects on firms' profits. The model is estimated for location choices in the video retail industry using a nested fixed-point algorithm solution. The results imply significant payoffs to product differentiation. Simulations illustrate the tradeoff between demand and intensified competition and the extent to which markets with larger product spaces, and thus more scope for differentiation, support greater entry.

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

JEL Classification: L0, L1, L2, L8

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1 Introduction

This paper studies firms' joint entry and product-type choices in retail markets where location choice constitutes a form of product differentiation. While previous studies of entry have modeled the trade-off between the available demand in a market and the intensity of competition faced by a new entrant in that market due to its attractiveness to incumbents, the strategic importance of product-type choice within a market has received less attention. For example, Bresnahan and Reiss (1988, 1991) and Berry (1992) show that the equilibrium number of firms in a market increases in response to increases in market demand and firms experience a decline in profits due to the entry of additional competitors. Since the authors consider well-defined, homogeneous products and markets, the firms in their studies have no scope to offer customers differentiated products. In industries with heterogeneous product and market characteristics, however, dissimilarities between competitors' products imply varying intensities of competition between firms. Research going back to Hotelling (1929) and Salop (1979) has shown how to incorporate such cases into spatial models to more accurately predict the number of firms that are supported in markets with product differentiation.

I consider how one specific product-type choice, namely the physical location within a market chosen by a retail firm, affects that firm's entry decision. As an instrument of product differentiation, a firm can strategically choose a location when entering a market to expose itself to as little competition as possible for any given level of market demand. The paper complements other recent applied work on the role of geography in microeconomic decision-making. Studies such as Davis (2001), Manuszak (2000), Pinske, Slade, and Brett (2002), and Thomadsen (2002) quantify the importance of spatial differentiation for own- and cross-price elasticities, taking the locations of firms relative to each other as given. While these studies explicitly focus on the post-entry competition stage between retail establishments, the empirical modeling approaches are very similar to the ones used here. The distance between consumers and stores is, for example, treated as a store characteristic that directly affects consumers' utility. Similarly, to readily measure such distances, the space that a market covers is divided into separate neighborhoods or locations along Census-delineated lines. The attractiveness of spatial location as a form of product differentiation rests on this use of physical distance as an objective measure of the dissimilarity between firms' products. The model in this paper can, however, be easily extended to other, more complex forms of product differentiation to study the role of optimal positioning in characteristic space on market structure more generally.

Modeling the joint choice of entry and product type is a complex problem. The industrial organization literature, such as Sutton (1991, 1998), has recognized that market structure reveals information about firms' underlying economic profits, which in turn provides information about the intensity of competition between firms in the market. Mazzeo (2002) builds upon this concept by noting that firms' product type choices provide additional information about the underlying competitive interaction between differentiated firms. His paper develops an equilibrium model of entry and quality-level choice.[1] An analytically appealing feature of his model is that firms possess complete information about competitors; however, the resulting Nash equilibrium concept is computationally difficult to verify for a large number of different product types. The application of the model to the motel industry shows that even with three quality levels, estimation becomes burdensome due to the large number of profit constraints that must hold in equilibrium.

Following Mazzeo (2002), I incorporate the effect on market structure of varying competitive intensities between differentiated products. In contrast to the complete information framework, however, the model presented here recognizes that idiosyncratic sources of profitability may be of importance in driving the location decision and, furthermore, that such firm-specific profitability may be difficult to observe by competitors with certainty. Examples include differences in firms' cost structures

[1] Related work in this area includes Ellickson (2003), Stavins (1995), and Toivanen and Waterson (2001b). For reviews of empirical research on discrete choice game-theoretic models, see Toivanen and Waterson (2001a) and Reiss (1996).

or their intangible assets, such as staff managerial talent, customer service, and inventory maintenance. Consequently, I allow firms to possess private information about their own profitability, which is observed by competitors only in distribution. Payoffs are thus a function of the firm's expectation of its competitors' optimal location choices, as well as its own idiosyncratic profitability. The resulting Bayesian Nash equilibrium conjectures over competitors' optimal location strategies, which represent the likelihood of entering a particular location rather than the exact location choice, can be derived more easily than the equilibrium in the complete information framework.[2] This set-up, therefore, facilitates the application of the model to a realistic, large-dimensional set of product types.

The model is applied to the location choices of video retailers in 151 medium-sized markets. Optimal store location is a strategic advantage in this industry because the cost of the transaction is small relative to the transportation costs that consumers incur. The empirical results bear out the intuition that firms use spatial differentiation to shield themselves from a large fraction of competitors in the market. Distant competitors are found to drive down payoffs significantly less than competitors close-by and such competitive interaction helps to explain the patterns of location choices found in the data. These data show that while highly populated areas are chosen by many firms, locations with less attractive demographic make-ups experience some clustering of firms as well. In the absence of competitive interaction between firms, however, firms' location choices would mirror the distribution of demand in the market more closely.

The significant payoffs to product differentiation imply that the scope for differentiation as measured by the market's area, or more generally, the overall size of the product space, may be an important

[2] The estimation of empirical auction models such as the symmetric independent private values model similarly relies on the computation (and inversion) of Bayesian Nash equilibrium bidding strategies to recover bidders' unobserved valuations of an object. Recent non-parametric approaches such as Guerre, Perrigne, and Vuong (2000) and Athey and Haile (2002) allow for greater flexibility in the assumptions governing the distribution of such valuations, which may also be of use in models such as the one estimated here. For recent surveys of this literature, see Hendricks and Paarsch (1995), Laffont (1997), and Perrigne and Vuong (1999).

determinant of market structure. To illustrate the importance of the size of the product space, I simulate, based on the estimated parameters, the effect on the entry process of the geographic dispersion of demand as a market's population and area grow. As the market area grows, the ability of firms to achieve greater localized market power through spatial differentiation is found to have a significant impact on overall entry. At the same time, however, payoffs from such differentiation are offset by the negative effect of reduced demand due to the dispersion of population in the increased market area. I find that for the specific example of the video retail industry with highly localized demand, the net effect of these two forces is that as a market's population and area grow, the number of firms supported by the market increases only slightly.

While these results apply only to medium-sized markets in the video retail industry, the model's relevance extends to other industries in larger geographic markets. In particular, the model may be of use in horizontal merger analyses to define the geographic boundaries of markets. By allowing the competitive interaction between firms to differ by finely partitioned distance ranges, the estimated competitive effects would indicate how large the distance between two firms has to be at a minimum for them to no longer exert any competitive pressures on each other. Such a distance cut-off is of help in demarcating the geographic boundaries of such firms' competitive environment in a given city. Since the model treats location as a product attribute, the complimentary questions that arise in horizontal merger analyses of the relevant product market can be analyzed similarly for other non-spatial product characteristics.

Section 2 presents the model of entry and location choice and section 3 describes the data set used for estimation. Section 4 presents a set of estimates for a model of entry that ignores the effect of product differentiation. In section 5, I outline the estimation routine and present some base-line results and counterfactual exercises. Section 6 concludes with a discussion of the main features of the model and their economic implications.

2 Model

2.1 Motivation and Set-up

The use of discrete strategic games in empirical modeling has to date been limited. Manski (1993) points to the mutual dependence of agents' choices on each other as a major difficulty in empirically implementing models with strategic interactions or endogenous effects. This interdependence makes the application of such models to individual firm behavior more difficult as it oftentimes entails the existence of multiple equilibria to the discrete game.

The existing literature has dealt with the multiplicity of equilibria in several ways. Tamer (2003) builds upon earlier work by Jovanovic (1989) to derive an upper and a lower bound for the probability of observing each non-unique outcome of the game. By imposing support conditions, the model's parameters are point identified and can be estimated using a semi-parametric maximum likelihood estimator such as the one suggested in Manski and Tamer (2002). Andrews and Berry (2003) and Ciliberto and Tamer (2003) suggest a related approach that identifies bounds rather than point estimates of the parameters of interest. Ciliberto and Tamer (2003) also present a first empirical application of these procedures that studies airline market structure.

Work by Berry (1992), Bresnahan and Reiss (1991), and Berry and Waldfogel (1999) suggests instead to specify a model that combines multiple equilibria for individual players' actions into one joint equilibrium that can be uniquely predicted. In the entry context, for example, such models are able to uniquely predict the equilibrium number of entrants into a market, but not the identity of such entrants. Symmetry assumptions are necessary to generate a unique prediction for the equilibrium number of entrants, namely that firms' profits are invariant to permutations of the entry decisions made by their opponents. Mazzeo (2002) relaxes this symmetry assumption by introducing firms whose products are differentiated into discrete types and conditions the analysis on the number of firms of each type that enters. The complete information nature of his model makes it computationally infeasible, however, to extend the analysis to more than three types of firms.

This paper instead develops a strategy of estimating discrete strategic games by allowing for asymmetric information about players' payoffs. Analyzing discrete strategic interactions in an incomplete information framework was first suggested by Rust (1994) in the context of discrete dynamic multi-player games. I apply his framework to the computationally simpler static set-up, in line with much of the empirical literature on entry. As pointed out by Rust (1994), the main advantages of the imperfect information framework are that equilibrium strategies can be easily computed for a large-dimensional set of product types. While the assumption of imperfect information does not rule out the existence of multiple equilibria per se, simulation evidence shows that the specific application of the model to spatial location choice eliminates such multiplicity.

At the beginning of the period, each firm makes its joint entry and location choice based on expected post-entry profits. These profits are driven by two opposing forces. On the one hand, favorable demand characteristics of a location attract firms to that location. At the same time, the increased concentration of firms at that location adversely impacts firm profits due to greater competition. Following Manski (1993), the dependence of firm behavior on the behavior of rivals in the market is treated as an endogenous effect highlighting that the choices of one player affect the choices of another. Firm profit is thus specified as a function of the demand in the firm's location, as well as the equilibrium location choices of all other competitors in the market.

Profits are also allowed to vary between firms in the same location on account of differences in cost structures and other firm-specific sources of profitability, which are assumed to be ex-ante observed only by the firm itself. This assumption regarding incomplete information about competitors' profitability is reasonable; for example, the managerial talent of a firm's employees cannot be easily observed by competitors who must separate the role of such intangible assets in a firm's success from other related profit shifters. Entry and location choices are thus determined by the demand characteristics of the market, firms' expectations of their competitors' optimal location choices, and each firm's idiosyncratic profitability.

2.1.1 Sequence of Moves

Firms' entry and location choices are analyzed as a discrete choice problem. A set of F potential entrants simultaneously chooses whether or not to enter a market m and where within the market to locate. The number of potential entrants exceeds one and is commonly known by all F players. For simplicity, firms are assumed to make independent entry and location choices.[3] The set of possible locations in the market is indexed by $l = 0, 1, ..., L^m$, which includes the decision not to enter given by $l = 0$. The locations are thus discrete and each location can accommodate more than one firm. Figure 1 displays the decision tree. Firm f's location decision, with $f = 1, ..., F$, is denoted by $\boldsymbol{d}_f$, where $d_{fl} = 1$ if location l is chosen, 0 otherwise.

2.1.2 Payoffs

Upon entry, firm f's payoff in location l in a market m is given by the following reduced form:[4]

$$\begin{aligned} \Pi_{fl} &= \boldsymbol{X}_l \boldsymbol{\beta} + \xi + h(\Gamma_{.l}, \boldsymbol{n}) + \varepsilon_{fl} \qquad (2.1) \\ &= \overline{\Pi}_l + \varepsilon_{fl} \end{aligned}$$

[3]The model thus ignores one dimension of the decision-making process for multi-product firms and chain stores, namely the potential for cannibalization of revenues of existing products or established stores when introducing a new product or opening a new outlet. The significance of this assumption will depend in each case upon the particular empirical setting.

[4]This specification of the profit function is chosen primarily to simplify estimation given the unavailability of firm-level market shares. This limitation on available data is shared by other work in the field, such as Berry (1992) and Bresnahan and Reiss (1991). To model homogeneous product markets, they use a similar payoff function interpreted as the log of a market size/demand term multiplied by a variable profit term that depends on the number of market competitors. Correspondingly, the empirical setting in this paper is an industry with a product that could be viewed as homogeneous, while store characteristics, and in particular stores' locations, are the main factors of differentiation between firms. For an example of a study that uses firm-level market share information, see Berry and Waldfogel (1999).

where market superscripts m have been omitted to simplify the exposition. The first two terms represent demand characteristics that affect payoffs in location l. $\boldsymbol{X}_l$ is a vector of demand and cost characteristics specific to location l, including population and median rent. Since the demographic characteristics that can be observed by the econometrician may not reflect all cost and demand factors driving firm profitability, unobservable exogenous differences across markets are captured by a market-level effect, ξ, which is a random draw from the known distribution $G(\cdot)$. All cost and demand shifters including ξ are known to the firm and its competitors at the time of decision making. The next term, $h(\Gamma_{.l}, \boldsymbol{n})$, captures the effect on profits due to competition from all rivals in the market. Non-uniform competitive interaction between different product types requires, in the case of space as a differentiating characteristic, a two-dimensional matrix of competitive effects by location pairs.[5] Therefore, Γ is an $L \times L$ matrix of competitive effects; for example, the lth column of Γ, $\Gamma_{.l}$, represents the competitive intensity between competitors in locations 1 through L and a firm in location l. The impact on payoffs due to competition from other firms is thus a function of $\Gamma_{.l}$ and $\boldsymbol{n}$, where $\boldsymbol{n}$ is a vector containing the number of firms in each of the L locations in the market. Mean profits from not entering, $\overline{\Pi}_0$, are normalized to zero across firms and markets.

ε_{fl} represents the idiosyncratic component of firm f's profits from operating in location l. The asymmetry of information between firms arises from this idiosyncratic profitability (their "type"), which is treated as a realization of a random variable whose distribution is common knowledge among all competitors, but whose value is private information to the firm. Following Rust (1994), players' information sets and types are defined by the following assumption:

> (A1) *Independent symmetric private values:* Players' profitability types ε_1, ...,ε_F are private information to the players and are independently distributed draws from the same prior distribution $G(\cdot)$.

[5] A similar matrix approach can be used in other multi-dimensional characteristic spaces provided an appropriate distance metric, corresponding to physical distance in the current application, measures the dissimilarity between firms' products.

In this specification, ε, a firm's type, captures *all* differences between it and other potential entrants. The payoff function thus retains some of the symmetry underlying the payoff functions common to the empirical entry literature. As a result, profits depend only on the number of entrants at every location, and not on the entrants' identities.[6] The symmetry assumption implies that each pair of firms will have the same conjecture about the profitability of a third firm and the profitability of any pair of firms is identically distributed.

For the purposes of estimation, I make the following assumptions, which allow an identical profit function to be applied to every location in the market and across markets with varying numbers of locations:

(A2) $h(\Gamma_{.l}; \boldsymbol{n}) = \sum_{k=1}^{L} \gamma_{kl} n_k$.

(A3) $\gamma_{kl} = \gamma_{k'l} = \gamma_b$ if $d_b \leq d_{kl},\ d_{k'l} < d_{b+1}$, where d_b and d_{b+1} denote cut-offs that define a distance band.

Assumption (A2) implies that competitors' effects are additively separable across locations and, furthermore, that the incremental impact on payoffs of an additional firm in a given location is constant. This is in contrast to previous work by Berry (1992) and Bresnahan and Reiss (1991) who employ more flexible functional forms that allow for $h(.)$ to be decreasing in $\boldsymbol{n}$ at a declining rather than constant rate. Relaxing assumption (A2) is of computational rather than conceptual difficulty. Since there is ex-ante uncertainty over rivals' location choices, the firm needs to form an expectation of how many competitors it will face in each location. The linear specification in (A2) simplifies the computation of the expected competition from all firms, the importance of which will become clear in the later discussion of the equilibrium in the model.

[6] Symmetry is maintained in this paper solely for computational reasons. It can be relaxed to allow for more heterogeneous payoff functions. Einav (2003), for example, estimates a sequential, Bayesian timing game applied to heterogeneous movie producers' choices of movie release dates.

Assumption (A3) accommodates irregularities in the data that affect estimation of the model. The sample market locations, as further described in Section 3, consist of population-weighted centroids of 1990 Census tracts. Census tracts vary in area and shape due to differences in population between tracts as well as regional differences in city planning. The irregularity of Census tracts implies that no two tract centroids are at the exact same distance from each other as others in the market, as illustrated in figure 2, which depicts the tracts that make up one of the sample markets, Wilmington, NC. Assumption (A3) implies that firms located in different cells, k and k', but within a given distance range from location l have the same impact on the profitability of firms in location l, across locations in a market and across markets.[7] As a result, rivals located in tracts within a certain distance band around location l exert the same competitive pressure on a firm in location l.

Allowing for a maximum of B distance bands, indexed by $b = 0, 1, ..., B$, the resulting payoff function is given by:

$$\Pi_{fl} \quad = \quad \xi + \boldsymbol{X}_l \boldsymbol{\beta} + \sum_b \gamma_b N_{bl} + \varepsilon_{fl} \tag{2.2}$$

In equation 2.2, γ_b represents the impact of competitors in distance band b. γ_0 measures the competitive effect of firms at a distance between zero and d_1, γ_1 the competitive effect of firms at a distance between d_1 and d_2, and so forth.[8] The aggregate number of firms in locations within each of these distance bands is given by N_b. Specifically, $N_{bl} = \sum_k \mathbb{I}^b_{kl} n_k$, where $\mathbb{I}^b_{kl} = 1$ if $d_b \leq d_{kl} < d_{b+1}$ and 0 otherwise.

[7] 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 l will be the same as the competitive pressure of two firms, of which one operates in the cell directly north of l and one in the cell directly south of l. Ideally, the first scenario would be more attractive to firm f than the second; however, in the current treatment of competitive impacts, there will be no difference.

[8] The differences in area between small city center tracts and larger tracts at the outskirts imply that a firm's immediate competitors are not identified uniformly across locations if only competitors in the same location as the firm are included as such immediate competitors. Instead, I set the effect of competitors in the first distance band around a firm's location to be the same as that of competitors in the firm's own location. Given a short radius for the first distance band, this modification will not, in most cases, include tracts other than the tract in which the firm is located, but will only affect city centers where adjacent tracts are sufficiently close.

2.2 Equilibrium Location Conjectures

2.2.1 Derivation of Equilibrium Location Conjectures

This section first analyzes firms' equilibrium location choices, conditioning on the total number of firms that have decided to enter the market. The entry decision is discussed further in section 2.3. The location decision is complicated by the fact that under an imperfect information framework, a firm can only form an expectation of its rivals' optimal location choices. The actual location choice of a rival firm is determined by its realized idiosyncratic profitability type. Assuming that E firms have decided to enter the market, in equilibrium, every firm will have the same expectation of its $(E-1)$ competitors' location choices. Based on this expected competitor distribution across all locations, each firm will choose the location that maximizes its payoffs given its realization of its own profitability type. The symmetric Bayesian Nash equilibrium in this model is therefore the optimal response that maximizes the firm's expected payoff conditional on entry, given its self-confirming conjecture about other competitors' strategies.

For each firm f, the pure-strategy Bayesian Nash equilibrium location choice, δ_f, is given by:

$$\delta_f(\varepsilon_f) \in \arg\max_{d_f} \sum_{\delta_{-f}} \overline{\Pi}_f(d_f, \delta_{-f}) \Pr(\delta_{-f}|\xi, \boldsymbol{X}, E, \theta_1) + \varepsilon_f \tag{2.3}$$

where (d_f, δ_{-f}) denotes the value of the profile when firm f chooses strategy d_f evaluated at the firm's type vector, ε_f, and the other players follow strategy δ_{-f} evaluated at their type vectors, ε_{-f}.[9] The payoff function parameters $(\boldsymbol{\beta}, \gamma)$ have been combined into θ_1. The assumption of independent types implies that the joint probability of δ_{-f} simplifies to:

$$\Pr(\delta_{-f}|\xi, \boldsymbol{X}, E, \theta_1) = \prod_{g \neq f} p_g(\delta_g|\xi, \boldsymbol{X}, E, \theta_1) \tag{2.4}$$

$p_{gl}(\cdot)$ denotes the prior probability that firm g will choose location l. Applying assumption (A2)

[9] See Fudenberg and Tirole (1991), pp. 209-241.

that competitors impact a firm's profits linearly yields the expected payoff in location l:[10]

$$\mathbb{E}[\Pi_{fl}] = \xi + \boldsymbol{X}_l\boldsymbol{\beta} + \sum_b \gamma_b \mathbb{E}[N_{bl}] + \varepsilon_{fl} \tag{2.5}$$

where the expected number of firms per distance band, $\mathbb{E}[N_{bl}]$, equals:

$$\mathbb{E}[N_{bl}] \;\; = \;\; \sum_k \mathbb{I}^b_{kl}\mathbb{E}[n_k] = \sum_k \mathbb{I}^b_{kl}(E-1)p_{gk} + \mathbb{I}_{b=0} \tag{2.6}$$

The number of competitors that firm f expects to face in location l equals $(E-1)p_{gl}$. The indicator variable $\mathbb{I}_{b=0}$, set equal to one for distance band $b=0$ and zero for all remaining distance bands, reflects that the number of firms in distance band $b=0$ includes firm f itself were it to choose location l.

Due to the symmetry of rivals' types, firm f's probability assessment of g's optimal location strategy will be the same across all competitors. This probability is given by:

$$p_{gl}(\delta_g|\xi, \boldsymbol{X}, E, \theta_1) = \Pr(\mathbb{E}[\overline{\Pi}_{gl}(\cdot) + \varepsilon_{gl}] \geq \mathbb{E}[\overline{\Pi}_{gk}(\cdot) + \varepsilon_{gk}], \forall\ k \neq l,\ \forall\ g \neq f) \tag{2.7}$$

For the sake of computational tractability, I assume that players' types, ε, are i.i.d. draws from a type 1 extreme value distribution.[11]

The scale parameter of the extreme value distribution captures the degree of uncertainty that a firm has over its rivals' profitability draws. In the limit, as it tends to zero, profitability draws across locations are perfectly correlated and concentrated at the distribution's mean. In this case, there is

[10] Note that relaxing assumption (A2) to incorporate a more desirable functional form for $h(\gamma, n)$ that decreases in n at a declining rate rather than linearly would involve the use of more complicated numerical integration techniques.

[11] As suggested by Rust (1994), the extreme-value specification is attractive in this context because it entails closed-form expressions for players' choice probabilities. The computational tractability of i.i.d. Logit draws comes at a cost, however. It implies, for example, that firm profitability is uncorrelated across *firms* within a given location, as well as across *locations* for a given firm. Thus the specification does not consider that profitability is likely to exhibit spatial correlation since demand characteristics are spatially correlated. If such patterns were of importance, the estimated competitive effects would be biased downwards. To allow for more realistic substitution patterns across locations, a more flexible error distribution could be used. Most appropriate distributions, such as the multinomial normal distribution, do not yield closed-form solutions for the vector of location probabilities. As a result, the equilibrium probabilities would have to be found via multi-dimensional numerical integration or simulation nested in the fixed-point algorithm, which would significantly increase the computational complexity of the problem.

no uncertainty about rivals' profitability and McKelvey and Palfrey (1995) show that the outcome of the game approaches the one of the corresponding perfect information model. In the empirical estimation, the scale parameter is not separately identified from the remaining parameters of the pay-off function and is therefore normalized to one. This results in traditional multinomial Logit location probabilities for firms' beliefs, conditional on the entry of E firms. Therefore,

$$p_{gl}(\delta_g|\xi, \boldsymbol{X}, E, \theta_1) = \frac{\exp(\mathbb{E}_g[\overline{\Pi}_{gl}])}{\sum_{k=1}^{L} \exp(\mathbb{E}_g[\overline{\Pi}_{gk}])} \tag{2.8}$$

The remaining rivals in the market similarly form their belief of firm f's best response. The assumption of symmetric types implies that in equilibrium $\boldsymbol{p}_g{=}\boldsymbol{p}_f{=}\boldsymbol{p}^*$. A firm's vector of conjectures over all locations l is defined by the following set of L equations:

$$\begin{aligned} p_l^*(\delta|\xi, \boldsymbol{X}, E, \theta_1) &= \frac{\exp(\boldsymbol{X}_l\boldsymbol{\beta} + \gamma_0 + (E-1)\sum_b \gamma_b \sum_j \mathbb{I}_{jl}^b p_j^*)}{\sum_{k=1}^{L} \exp(\boldsymbol{X}_k\boldsymbol{\beta} + \gamma_0 + (E-1)\sum_b \gamma_b \sum_j \mathbb{I}_{jk}^b p_j^*)} \\ \forall\, l &= 1, ..., L \end{aligned} \tag{2.9}$$

where the expressions for the expected number of firms per distance band have been substituted into the payoff function. Note that the market level effect, ξ, does not determine sorting into locations. Since ξ is invariant across locations within a market, it does not scale the relative attractiveness of one location to another. The equilibrium location conjectures thus result from the system of L equations defined in equation 2.9, which makes up a fixed-point mapping from the firm's conjecture of its competitors' strategies into its competitors' conjectures of the firm's own strategy. The following section illustrates how equilibrium conjectures are incorporated into the expected payoff function.

2.2.2 Illustration

Figure 3 depicts a square-shaped market made up of nine locations which are grouped into three distance bands. The immediate competitors are only those in the firm's own location. The neighboring competitors, namely those in band 1, of a firm located in cell seven are the firms located in cells four, five, and eight, while the most distant competitors are located in cells one, two, three, six, and nine. Based on equation 2.5, $\mathbb{E}[\overline{\Pi}_7]$ is given by:

$$\mathbb{E}[\overline{\Pi}_7] = \xi + \boldsymbol{X}_7\boldsymbol{\beta} + \gamma_0 + (E-1)(\gamma_0 p_7^* + \gamma_1(p_4^* + p_5^* + p_8^*) + \gamma_2(p_1^* + p_2^* + p_3^* + p_6^* + p_9^*)) \qquad (2.10)$$

Assuming that the competitive impact of neighboring firms, γ_1, exceeds the impact of more distant firms, γ_2, the appeal of cell seven lies primarily in its placement at the edge of the city with a small set of immediately adjacent locations and competitors. On the other hand, a firm located in cell five will have many close-by competitors, exposing it to stronger competition than a firm located on the city's fringe. At the same time, from a demand perspective, cell five is more attractive than cell seven because it grants easy access to most of the consumers in the market living in its own and neighboring locations. The equilibrium firm location pattern is then determined by this trade-off between demand and competitive pressures.

2.2.3 Equilibrium Properties

Equation 2.9 sets up a continuous mapping from the L-dimensional simplex into itself. Due to the constraint that probabilities sum to one, the system reduces to $(L-1)$ equations in $(L-1)$ unknown conditional location probabilities. Entrants' equilibrium location probabilities that result from this system in turn map into firms' optimal strategies. Since firms' own conjectures are contained in the probability simplex and are continuous in competitors' expected behavior, the existence of at least one solution to the system of equations follows immediately from Brouwer's Fixed Point Theorem. To establish the uniqueness of such a solution to the system of conditional location choice probabilities,

$$\Psi(\boldsymbol{p}, \boldsymbol{X}, E) = \boldsymbol{p} - F(\boldsymbol{p}, \boldsymbol{X}, E) = 0, \qquad (2.11)$$

it is sufficient to show that the matrix of partial derivatives of Ψ with respect to $\boldsymbol{p}$ is a positive dominant diagonal matrix, or that

$$1.\quad \frac{\partial \Psi_l}{\partial p_l} > 0$$
$$2.\quad \left|\frac{\partial \Psi_l}{\partial p_l}\right| \geq \sum_{k \neq l} \left|\frac{\partial \Psi_l}{\partial p_k}\right|$$

Consider first the simplest example of a 2×2 city that allows for spatially differentiated competition by letting the effect of competitors in a given location to be different from that of competitors in the remaining three locations.[12] Normalizing $p_4 = 1 - (p_1 + p_2 + p_3)$, the matrix of partial derivatives for this specific example contains the elements

$$\frac{\partial \Psi_l}{\partial p_l} = 1 - (E - 1)p_l(\gamma_0 - \gamma_1)(1 - p_l + p_4) \tag{2.12}$$
$$\frac{\partial \Psi_l}{\partial p_k} = -(E - 1)p_l(\gamma_0 - \gamma_1)(-p_k + p_4) \tag{2.13}$$
$$k \neq l,\ l, k = 1, 2, 3$$

Assuming without loss of generality that $p_4 = \min(\boldsymbol{p})$, conditions 1. and 2. can be established provided that the number of entrants exceeds one, or $E > 1$, and provided that $\gamma_0 < \gamma_1$. Consequently, the location choice game for the 2×2 city has a unique equilibrium as long as immediate competitors that are located in the same cell drive profits down by more than more distant competitors. This simple example is suggestive of settings that entail multiple equilibrium location strategies. In particular, if competition between firms were to actually intensify as they move further away from each other, there may be many locations in which a firm would face the same expected number of distant competitors and thus an identical competitive environment. Similarly, uniqueness may break down in the case where there are positive spill-overs to clustering, that is γ_b is positive. Non-uniqueness arises in these scenarios in particular if there are only little or no differences in locations' demographic make-up to induce additional variation in pay-offs across locations.

[12] Expected profits for this example are thus given by

$$\mathbb{E}[\Pi_{fl}] = \xi + \boldsymbol{X}_l\boldsymbol{\beta} + \gamma_0(1 + (E-1)p_l) + \gamma_1(E-1)\sum_{k \neq l} p_k + \varepsilon_{fl}$$

for $l, k = 1, ..., 4$.

For the general profit function in equation 2.2, the elements of the matrix of partial derivatives are significantly more complex as they involve locations in additional distance bands. Allowing for three distance bands and a total of L locations, the partial derivatives of Ψ are given by:

$$\begin{aligned} \frac{\partial \Psi_l}{\partial p_l} &= 1-(E-1)p_l[(\mathbb{I}^1_{lL}(\gamma_0-\gamma_1)+\mathbb{I}^2_{lL}(\gamma_0-\gamma_2))(1-p_l+p_L) \\ &\quad +(\gamma_1-\gamma_2)(\sum_{k\neq l}(\mathbb{I}^2_{kl}(1-\mathbb{I}^2_{kL})-\mathbb{I}^1_{kl}(1-\mathbb{I}^1_{kL}))p_k)] \end{aligned} \tag{2.14}$$

$$\begin{aligned} \frac{\partial \Psi_l}{\partial p_k} &= -(E-1)p_l[(\mathbb{I}^1_{kL}(\gamma_0-\gamma_1)+\mathbb{I}^2_{kL}(\gamma_0-\gamma_2))(-p_k+p_L) \\ &\quad +(\gamma_1-\gamma_2)(\mathbb{I}^1_{kl}+\sum_{j\neq k}(\mathbb{I}^2_{jk}(1-\mathbb{I}^2_{jL})-\mathbb{I}^1_{jk}(1-\mathbb{I}^1_{jL}))p_j)] \\ &\quad k\neq l,\ l,k=1,...,L-1 \end{aligned} \tag{2.15}$$

where p_L has been normalized to $1-\sum\limits_{l\neq L} p_l$ and, as before, $\mathbb{I}^b_{kl}=1$ if $d_b \leq d_{kl} < d_{b+1}$ and 0 otherwise. The partial derivatives are a function of the vector of location probabilities that depends on the dispersion of locations within the market in a complicated way. For the general payoff function, it is thus difficult to establish analytical conditions that guarantee that the matrix of partial derivatives has a positive dominant diagonal. The functional form of the partial derivatives suggests, however, that exogenous determinants of $\boldsymbol{p}$ and the layout of locations relative to each other in a given market are critical factors in the existence of a unique set of location probabilities.

To investigate the sensitivity of the equilibrium to within-market variation in exogenous demographics, I apply the model to a simulated data set of markets with significant variation in demographics.[13] Equilibrium conjectures are found numerically using the method of successive approximations where the fixed point results from successively improving upon an initial guess for the probability vector until $[\frac{\exp(\overline{\Pi}_1(\boldsymbol{p}))}{\sum\limits_k \exp(\overline{\Pi}_k(\boldsymbol{p}))}, ..., \frac{\exp(\overline{\Pi}_L(\boldsymbol{p}))}{\sum\limits_k \exp(\overline{\Pi}_k(\boldsymbol{p}))}]'$ results in $\boldsymbol{p}$. The existence of a unique equilibrium can then be established numerically if successive approximations to the equilibrium always converge to the same solution, independent of the initial starting values.

[13] The simulations focus only on the case where γ_b is negative, that is where geographic proximity to other competitors decreases profits due to increased competition, rather than on the case of positive spill-overs from geographic proximity to other firms.

The simulations show that as long as competitive interaction becomes weaker with distance (γ_b is less negative for more distant bands), the equilibrium is unique, even if locations are fully homogeneous in demographics. Variation in exogenous demographics or a larger number of locations proves to be necessary in ensuring uniqueness, however, for cases where γ_b becomes more negative with distance implying an intensification of competition with distance.

Expressions 2.14 and 2.15 as well as the simulation evidence thus suggest that there are two major sources that lead to uniqueness in this model. First, heterogeneity in the demographics of nearby locations allows for a distinction of locations with similar sets of expected competitors. Second, the dispersion of locations over the market area implies that the sets of locations that define immediate, neighboring, and distant competitors differ across locations. There are thus few locations that have the same sets of competitors in the various distance bands. Furthermore, the demographics faced by neighboring and distant competitors of firm f, but not faced by firm f, provide additional exogenous variation for f's expected number of competitors. When applying the model to larger, real-world markets that are naturally made up of irregularly placed neighborhoods of varying characteristics, the simulation evidence suggests that concerns about the location conjectures' uniqueness can be alleviated. In particular if competitive rivalry is stronger between competitors that are more rather than less alike in terms of geographic proximity, implying a γ_b that decreases with distance, the equilibrium is shown to be unique, mirroring the analytic results for the case of a 2×2 city.

2.3 Accounting for the Endogeneity of the Number of Entrants

In equation 2.6, a firm's expected number of competitors in a particular distance band is a function of E, the number of entrants into a market. Endogeneity in E arises because a firm's payoff is a function of the number of entrants, while at the same time this payoff drives the firm's decision to enter the market. The aggregate of all such individual entry decisions determines the number of entrants.

The number of entrants in a free-entry equilibrium is the result of a no-profit condition. Each entrant earns non-negative profits, but any additional entrant would suffer losses. The predicted number of entrants into a market m is simply:

$$\widehat{E}^m = F \cdot \Pr(\text{entry}^m) \tag{2.16}$$

where $\Pr(\text{entry}^m)$ denotes the identical probability of entry into market m by all firms.

Entry by a firm into a market involves a comparison of a weighted average of payoffs across all locations to the normalized payoff of not entering. In addition to the location-specific characteristics of the market, a firm's payoffs are influenced by market-level factors that do not vary across locations. Such market-level factors are captured in the payoff function in 2.5 by ξ. A market with a high value of ξ, for example, will support a larger number of entrants. The larger number of firms then drives average profit levels down to be on par with those earned in the remaining markets. Given the assumption of i.i.d. extreme value profitability types, $\Pr(\text{entry}^m)$ is given by:

$$\Pr(\text{entry}^m) = \frac{\exp(\xi^m)\left[\sum_{l=1}^{L^m} \exp(\boldsymbol{X}_l^m \boldsymbol{\beta} + \gamma_0 + (\widehat{E}^m - 1)\sum_b \gamma_b \sum_k \mathbb{I}_{kl}^b p_k^{*m})\right]}{1 + \exp(\xi^m)\left[\sum_{l=1}^{L^m} \exp(\boldsymbol{X}_l^m \boldsymbol{\beta} + \gamma_0 + (\widehat{E}^m - 1)\sum_b \gamma_b \sum_k \mathbb{I}_{kl}^b p_k^{*m})\right]} \tag{2.17}$$

Equations 2.16 and 2.17 can be used to back out the realization of ξ^m that matches the equilibrium number of entrants predicted by the model, $\widehat{E}^m$, to the number of firms observed in the data. Solving equations 2.16 and 2.17 for ξ^m implies:

$$\begin{aligned} \xi^m = {} & \ln(\widehat{E}^m) - \ln(F - \widehat{E}^m) - \\ & \ln\left(\sum_{l=1}^{L^m} \exp(\boldsymbol{X}_l^m \boldsymbol{\beta} + \gamma_0 + (\widehat{E}^m - 1)\sum_b \gamma_b \sum_k \mathbb{I}_{kl}^b p_k^{*m})\right) \end{aligned} \tag{2.18}$$

Based on equation 2.18, an equilibrium realization of ξ^m can be found for every market, given $\widehat{E}^m$, which is set equal to the actual number of entrants in the market, and the potential number of entrants, F. The solution of using the market-level effect ξ to account for the endogeneity of the number of entrants follows the approach used by Berry (1994) and Berry, Levinsohn, and Pakes (1995) in their estimation of competition in differentiated product markets.

In contrast to earlier entry models, the estimation of entry probabilities relies directly on knowledge of the size of the potential entrant pool. Without specifying F, the model's parameters can econometrically not be identified. Determining the set of potential entrants empirically is difficult, however, since the observed data only includes actual entrants and not those that merely consider entering, but choose not to. Earlier studies of entry into retailing (Cotterill and Haller 1992) have dealt with this problem by setting the potential entrant pool equal to the number of major chains in the industry. In the case of video retailing, this assumption is harder to justify since non-chain affiliated retailers account for a significant fraction of all firms. The solution I adopt is to estimate the model by fixing the potential entrant pool exogenously at varying sizes.

At one extreme, with an infinite potential entrant pool, the fraction of firms entering the market is small. The market-level effect ξ^m adjusts, in this case, relative to the outside option's mean profitability, which is normalized to 0, to reflect the revealed low attractiveness of such a market. The reverse holds true in the case where every firm in the potential entrant pool decides to enter signifying a high value of ξ^m. In the empirical implementation of the model, different assumptions about the size of the potential entrant pool are reflected in the realized value of ξ^m in each market. These values for ξ^m determine the estimated parameters, μ and σ, of the distribution of ξ. The results presented in section 5 show that, based on this solution to incorporating F, the estimates of the remaining parameters that affect the location-specific component of payoffs are fairly robust to varying the size of the potential entrant pool.

3 Data

The model is applied to entry and product-type choices in the video retail industry using discrete location choices as product types. The video retail industry is well-suited for an analysis of location choice as an instrument of product differentiation. The transaction under consideration consists of the rental of a video tape, a homogeneous and relatively inexpensive good, with prices of the rental transaction ranging between $2 to $4 per tape. Since a video tape is standardized, stores differentiate themselves in other ways, including the variety and depth of inventory carried, the terms of the rental contract concerning the rental period, and drop-off convenience. The main avenue of differentiation arises, however, from spatial location since the small absolute differences in prices across stores make customers unwilling to travel a long distance to carry out the rental at a lower price. This paper concentrates entirely on the spatial dimension of product differentiation. Seim (2001) contains an extension of the model that captures other forms of differentiation by incorporating two types of firms, chain stores and non-chain affiliated stores, each of which represents a different mix of product characteristics that has found success in the marketplace.

3.1 Sample Markets

Spatial differentiation will only play a significant role in market structure if the market's population, or the available demand, is sufficiently large and geographically spread out that firms can use location strategically. According to research commissioned by the Video Software Dealers' Association (1998), the average customer travels only 3.2 miles for a round trip to a video store. The markets used in this study are selected, therefore, to provide adequate scope for spatial differentiation by firms, while not being so large that distant competitors would rarely, if ever, compete with each other for customers. To facilitate identification of competitors operating within each market as well as potential customers in the market, I focus on well-delimited cities or groups of cities with shared boundaries.

Starting from a universe of medium-sized cities or incorporated places with a population between 40,000 and 150,000 obtained from Census data, I include in the sample cities or small groups of cities where the largest city outside of the market within a distance of 10 miles has a population below 10,000 and the population of the largest city within 20 miles does not exceed 25,000 people.[14] This selection rule serves to exclude candidate cities if they are part of a suburban sprawl or in a metropolitan area, which complicates the identification of market boundaries. Cities in tourist regions are also excluded since the resident population accounts for only a small share of the potential customer base. Neighboring cities are assigned to the same market if they lie within 10 miles of each other and either share boundaries with a candidate city or consist of Census tracts whose areas overlap with both cities.[15] As an additional check that the chosen markets are sufficiently geographically isolated from other cities in the region, I visually inspect each candidate market using regional maps. The resulting set of markets consists of 151 cities/groups of cities drawn from most U.S. states with a slight under-representation of the North East. Market size as measured by the included incorporated places' total population ranges from 41,352 to 142,303 people with an average market size of 74,367 people.

Further discretization is required to give meaning to the concept of a location within a market. First, the selected markets are divided into non-overlapping cells among which firms choose their optimal location. Rather than superimposing a regular grid on each of the cities as in the example

[14] All distances are computed as great circle distances according to the Haversine formula. Based on latitude-longitude coordinate data, the distance between two points, a and b, is given by:

$$d_{a,b} = 2R \arcsin\left[\min\left\{\left((\sin(0.5(lat_b - lat_a)))^2 + \cos(lat_a)\cos(lat_b)(\sin(0.5(lon_b - lon_a)))^2\right)^{0.5}, 1\right\}\right]$$

where R denotes the radius of the earth. See Sinnott (1984).

[15] Census tracts are small subdivisions of counties rather than cities, which have an average size of 4,000 people. The area of any given tract may therefore overlap with the area of more than one city. Census tracts that overlap with the sample cities are identified using the Census Bureau's geographic correspondence engine *MABLE/Geocorr*, available at `http://www.Census.gov/plue/`. This program includes a mapping utility that is capable of providing a comprehensive list of Census tracts whose area overlaps with each of the chosen markets. These overlapping tracts are included as part of a market unless the area of overlap contains an insignificant proportion of the tract's total population.

of the square city discussed above, I choose to divide the markets into cells along more natural lines, namely Census tracts. While neighborhoods obviously change and shift over time, the use of Census tracts as cells comes closer to dividing the sample markets into coherent, internally homogeneous locations. Next, since consumers and firms are spread across the continuum of space of each of the Census tracts, instead of integrating over this geographic space, I place all consumers and firms at the population-weighted centroid of their tract.[16] Each market is thus made up of a set of irregularly scattered point locations within the market's boundaries. Finally, as discussed above, the classification of locations into product types is complicated by the irregularity in Census tract areas. Center-city neighborhoods are on average more densely populated compared to Census tracts at the outskirts of the city with more sparsely populated, larger areas. Accordingly, neighboring locations are defined to be all locations within a given distance range.

On average, a sample market consists of 21 tracts, ranging from markets with only eight tracts to markets with 49 tracts. The distance between tract centers within a market averages 3.5 miles using population-weighted centroids as tract centers. While the distance between a tract and its closest neighboring tract in the market is, on average, only 1.1 miles, the average distance to the furthest tract is 8.1 miles. Given the small distances that consumers are willing to travel to rent a video, these descriptive statistics indicate that the chosen markets are of an appropriate size to allow for spatial differentiation without being unrealistically large.

The use of Census tracts as market subdivisions also implies an inclusion of the city's surrounding population that resides in a tract at the edge of the city, but not within the city's official boundaries. This increases the average market size from 74,367 to 90,563 people. Given the geographic isolation

[16] I obtain population-weighted centroids from the Census Bureau. They are used instead of the more standard area-weighted centroids to capture where the majority of the tract's population lives. For locations at the edge of a city, tracts tend to be large in area with an associated drop in population density and the area-weighted centroids generally lie at a greater distance from the remaining tracts' centroids than in the case of population-weighted centroids. The use of area-weighted centroids would therefore significantly overstate the attractiveness of these locations to firms in the form of greater distance from competitors in other locations in the city.

imposed upon sample markets, the population living within the market represents a large fraction of the population residing in the general area and thus is a good approximation of the consumer base for which stores in that market compete.

3.2 Video Rental Demand

Since store-level data on tape rentals are unavailable to me, I use the demographic characteristics of individual locations as a proxy for video rental demand. According to industry sources, total video demand is a function of the market's population, but varies as well across income levels, family status, and to a lesser extent age groups.[17] These demographics are available from the Census Bureau's decennial Census of Population at a high level of geographic disaggregation, including Census tracts. The available firm-level data on location choices, which dates to 1999, is combined with demographic data from the 2000 Census of Population. In addition, a private data vendor, Advanced Geographic Solutions, provided data on tracts' business characteristics such as establishment counts across all industries and daytime working population. Comparable business summary statistics are generally not available from the Census Bureau at this level of geographic disaggregation. The overall business establishment counts are used in part to identify whether a tract is purely residential, namely if it does not contain any establishments. In such cases, the tract's population is included in market size indicators, but the tract itself is not included in the set of possible locations that firms can choose to enter.

Table 2 provides a summary of the key variables used to estimate the model. The demographic variables include the population in the the store's chosen tract and in its immediate neighborhood,

[17] Hasting's Book, Music and Video, Inc. 1998 Annual Report states: "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..." and the Video Software Dealers' Association (1998) claims: "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."

as well as the population residing in two bands around the chosen location. The use of the surrounding population reflects, in a reduced form, that people's shopping behavior is not confined to their immediate neighborhood, but may cover nearby areas. To capture income differences across locations, I use population-weighted average per-capita income of the tract and of locations around the tract, by distance band. The effects of other demand drivers, such as family status and proximity to a college or university, are more difficult to isolate at the tract level. Publicly available city planning records for a subset of the markets suggests that tracts with a high percentage of households with children or tracts that are home to a college tend to be protected by zoning ordinances, which prohibit firms from locating freely in such tracts. In the absence of detailed zoning data for the full set of markets, these residential tracts cannot be eliminated from the location choice set. Their inclusion in estimation confounds the role of family status and university locations as demand factors. The estimated effects of these demand drivers would not reflect the inherent attractiveness of such locations, but capture instead that regulation dictates that residential zones are never chosen by stores. Due to these difficulties in identifying potential locations, demographic characteristics other than population and per capita income are excluded from the estimation.

The attractiveness of a retail location stems partially from the easy accessibility and convenience that the location offers to consumers. 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 business density is used as a proxy for its commercial character. The use of business density as a catch-all proxy for the general business environment in the location also controls for the extent to which zoning laws enforce the residential nature of a tract. Location-specific costs to running a retail establishment take mainly the form of property costs and lease payments. Data on commercial rental costs is not available at as disaggregate a level as the Census tract, however; housing costs tracked by the Census Bureau are median residential rents. The use of median residential rents as a cost shifter in estimation had only limited success.[18] Consequently, the results laid out in section 5 use business density as the sole proxy for the role of the commercial environment in choosing a tract.

As table 2 shows, demographic and commercial characteristics of locations within a market differ significantly from each other. The observed variability in demographics facilitates estimation of the model proposed above and enhances the likelihood of observing a unique set of equilibrium location strategies.

3.3 Video Store Locations

Firm-level data on video store locations are obtained from American Business Disc 1999. This U.S.-wide semi-annual business directory contains information on establishment location, chain affiliation and lines of business and is derived from Yellow Page directories backed by phone inquiries.[19] To match up store locations with Census tracts, each store's address is initially geo-coded. The resulting latitude-longitude coordinates are then assigned to the corresponding Census tract.

Firms' entry and location patterns vary significantly by market size and area. On average, 13.68 video stores compete in a market; the smallest has four stores and the largest 33 stores. At the tract level, both clustering in central locations as well as dispersion into locations at the city's edges can be observed. A significant fraction of the locations within a market is not chosen by any firm, but there are also locations that are selected by up to nine firms. As a result, some firms face many nearby competitors, the maximum number of firms that are located within half a mile of a firm's

[18] The estimated effect of median rent levels on the likelihood of choosing a location was, as expected, negative, but insignificant.

[19] The information on firm counts and locations for the public video chains derived from the database is cross-checked against information contained in the respective firms' public SEC filings. For the six public chains in operation in 1999, the database contains more than 95% of the chains' outlets as per their 1998 fiscal year 10-K annual report. Furthermore, the total number of listed video retail establishments is 31,774. This number closely matches analyst estimates of the industry's size ranging from 30,000 to 35,000 outlets. See Advanstar Communications (various issues) and Video Software Dealers' Association (1998).

tract being ten stores. At the same time, some retailers choose isolated locations such that they do not face any competitors within a 10-mile radius. Within the market area, we observe that firms choose to locate both in the market's center and on its outskirts, the maximum distance from the city center reaching up to 15 miles.

The location statistics displayed in table 3 confirm the irregular distribution of firms. Figure 4 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. The map shows clearly the variability in the tracts' areas and populations. Figure 4 also shows the number of competitors operating in each of the Census tracts as well as in three distance bands around one of the market's locations. The two concentric circles around the tract depict the bands containing immediately neighboring locations, as well as adjacent locations, which are between d_0 and d_1 miles away from the location.

In summary, the data available for estimation consist of a scattered set of point locations within a market, the number of stores operating at those locations, as well as the locations' demographic characteristics. Furthermore, based on distances between all L locations in the market, firms' competitors in the various distance bands are computed using pre-determined distance cut-offs.

4 Market-level Determinants of Entry

Before turning to the estimation of the model laid out in section 2, I present results that document aggregate patterns of entry at the level of the market. Market-level entry models put forth in the literature focus on the role of the intensity of competition between firms in determining equilibrium market structure in markets of varying sizes. These models assume that the competitive environment is uniform across firms since their product is homogeneous. Differences between firms may be incorporated on the cost side in the form of heterogeneous fixed costs to entry, which are observed perfectly by all competitors. Following the set-up used in Bresnahan and Reiss (1991), a representative firm among a set of n competitors operating in market m earns profit of the form:

$$\Pi_{mn} = S_m V_{mn}(X_m; \alpha, \beta) - F(W_m; \gamma) + \varepsilon_m \tag{4.1}$$

A competitor's total variable profit is the product of market size, S_m, and variable profit from serving a representative consumer, $V_{mn}(X_m; \alpha, \beta)$, which incorporates the effect of demographic shifters, X, on profit. Furthermore, each additional entrant, i, decreases variable profit by an incremental amount, α_i, resulting in a variable profit function of $V_{mn} = \alpha_1 + X_m\beta + \sum_{i=2}^{n} \alpha_i$. Total variable profit thus directly reflects market structure. $F(W_m; \gamma)$ denotes fixed costs in the form of operating costs or barriers to entry, which are, for simplicity, assumed to be identical across firms and market structures.[20] Last, ε_m represents unobservable components of profit that are drawn from an i.i.d. normal distribution.

To identify the parameters of the model, an equilibrium assumption is imposed that all n active firms in a given market have to earn non-negative profits, while any additional entrant would be unprofitable. The distributional assumption on ε_m then gives rise to an ordered Probit model of the equilibrium number of entrants, which is econometrically identified through cross-market variation in the observed number of competitors.[21]

The video retail sample covers markets with both a higher average number of competitors and a significantly wider range of market structures than the kinds of markets considered in the original application. Empirically, the competitive impacts, α, can only be identified for market structure categories that are sufficiently represented in the data. Since only nine markets have less than six active competitors, these are combined into a reference category with $n \leq 5$.[22] Furthermore,

[20] Bresnahan and Reiss (1991) allow fixed costs to increase with the equilibrium number of entrants into a market to capture that earlier entrants may be more efficient than later entrants. Due to the wide variation in the total number of entrants across sample markets this approach proves difficult to implement in the current setting.

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

[22] Profit for markets with five competitors is normalized to zero.

I combine markets with ten and eleven, twelve and 13, and 14 through 17 competitors into one category each and assume that additional entrants beyond the 18th firm do not depress profit any further. This results in a total of eight competitive effects that allow profit to vary across these market structures.

To be comparable to the results from the location-choice model presented in section 5, the total population across each market's Census tracts approximates market size S_m, population-weighted per capita income is used as a demographic profit shifter, X_m, and the tracts' area-weighted average business density is used as a cost shifter W_m. Table 4 displays the results of the ordered Probit estimation. The demographic parameters are significant and have the anticipated signs. The competitive impacts are consistently negative, driving down profits as more firms enter. However, they are not statistically significant, possibly due to the large number of competitive effects that need to be estimated to cover the range of market structures represented in the data.

Bresnahan and Reiss (1991) use the concept of a zero-profit equilibrium level of demand or entry threshold to measure the rate at which oligopoly profits decline. An entry threshold expressed in terms of market size captures the minimum level of demand each firm would require in equilibrium to break even. A comparison of entry thresholds across different market structures provides evidence of the extent to which margins decline as the number of competitors increases. Bresnahan and Reiss (1991) find, for example, that for the set of professional services industries they study, a monopolist on average requires 39% fewer customers to break even than a duopolist in the more competitive environment. Bresnahan and Reiss (1991) find also that by the time a market has three or more competitors, per-firm entry thresholds do not increase any further. For small markets with fewer than three competitors, this implies a nonlinear relationship between total market size and the equilibrium number of competitors, with the number of competitors increasing in population at a decreasing rate. For larger markets, however, the relationship between market size and number of firms is approximately linear.

The bottom panel of table 4 contains corresponding entry thresholds at the level of the market and the firm for the sample video retailers. For market structure categories that span two or more different firm counts, such as the category that includes both ten and eleven competitors, per-firm entry thresholds are computed at the average firm count for markets in that category. The per-firm entry thresholds suggest that across markets, each video retailer requires a population base of approximately 7,000 people to break even. In contrast to the small markets covered by Bresnahan and Reiss (1991), even in the smallest markets in the sample, at least four video stores are in operation. The entry thresholds are very similar across markets with different numbers of firms.[23] These findings are consistent with Bresnahan and Reiss's (1991) results for larger markets, in that they entail an approximately linear relationship between market size and equilibrium number of competitors for the specific range of video store market structures covered by the sample.

Bresnahan and Reiss (1991) suggest several reasons for constant per-firm entry thresholds. In homogeneous product industries, entry thresholds decrease in firm margins and entrants' efficiency. The proportional entry thresholds they find suggest that once a market has grown in size to three or more entrants, margins no longer change significantly. This set-up applies well to the extremely small local markets and professional service industries considered in the study. In differentiated product industries, however, similar entry thresholds across markets of varying sizes may simply indicate that product differentiation offsets competitive decreases in margins with larger numbers of competitors. This alternative explanation put forth in Bresnahan and Reiss (1991) is explored further in the remainder of the paper, using the above model of location choice. While the video retail industry exhibits similar features to the industries in earlier studies and is therefore arguably a homogeneous product industry, the larger geographic extent of the sample markets nevertheless awards firms an opportunity for product differentiation. The location-choice model allows for a

[23] A likelihood ratio test based on a restricted model that enforces equal entry thresholds across all firm count categories yields a test statistic of $22.32 \sim \chi(7)$, allowing us to reject the null hypothesis of full threshold proportionality across all market structures, however.

detailed analysis of the importance of such differentiation in entry decisions at a disaggregate neighborhood level in markets with a larger number of competitors.

5 Estimation and Results

5.1 Estimation

For the purposes of estimating the location-choice model, firms are placed into one of three distance bands and the distance cut-offs that define these bands are set to $d_0 = 0.5$ miles and $d_1 = 3$ miles, in accordance with Video Software Dealers' Association (1998) figures on customers' travel patterns. Thus, immediate competitors include all firms located within one half of a mile from each other and neighboring competitors those between one half and three miles from each other. Since the markets vary significantly in their area and thus in the maximum distance between tracts, the band covering the most distant locations is defined only with respect to the minimum distance that a pair of tracts has to satisfy to fall within that band. All firms in the city competing at a distance of more than, in this case, three miles from one another will have the same incremental impact on profitability. Given the localized nature of video rental demand, this assumption appears justified for the chosen cutoff value. Experimenting with the cutoff between the neighboring and remaining categories had only small quantitative effects on the results.

Thus, the payoff function that is taken to the data is:

$$\Pi_{fl} \quad = \quad \xi + \boldsymbol{X}_l\boldsymbol{\beta} + \gamma_0 N_{0l} + \gamma_1 N_{1l} + \gamma_2 N_{2l} + \varepsilon_{fl} \tag{5.1}$$

The demographic characteristics contained in $\boldsymbol{X}$ are each band's total population and average per capita income, as well as its business density.

Given observations on a cross-section of M markets, each of which is treated as an independent F^m-player location game, the likelihood function is given by:

$$L(\theta_1, \theta_2) = \prod_{m=1}^{M} \boldsymbol{p}_{\theta_1}(\boldsymbol{d}^m | \xi^m, \boldsymbol{X}^m, \widehat{E}^m) g_{\theta_2}(\xi^m | \boldsymbol{X}^m, \widehat{E}^m, F^m) \tag{5.2}$$

where $\boldsymbol{d}^m = (d_1^m, d_2^m, ..., d_{F^m}^m)$ denotes the vector of actions taken by the F^m players in market m. The likelihood function consists of two parts. The first part computes the likelihood of observing entrants' location choices conditional on the market-level effect ξ^m. To derive the unconditional likelihood, I integrate over the distribution of ξ^m, $G(\cdot)$. ξ^m is assumed to be an i.i.d. draw from a normal distribution with mean μ and standard deviation σ. The density of each observation ξ^m is denoted by g_{θ_2}, with $\theta_2 = (\mu, \sigma)$.

Estimation of the model involves two steps. For a given set of values for the parameter vector (θ_1, θ_2) and the tracts' demographic data, the system of equations in 2.9 is solved numerically for its fixed point for each of the markets in the sample. Successive approximations to the fixed point result in a vector of equilibrium location choice probabilities, $\boldsymbol{p}^m$.[24] The equilibrium location choice probabilities, together with $\widehat{E}^m$ and F, feed into equation 2.18 to yield an equilibrium realization of the market-level unobservable ξ for each market m.

The optimal parameter values then are found by nesting the fixed point algorithm into a maximum likelihood routine to find the optimal parameters that explain the observed location patterns. The parameters to be estimated include both $\boldsymbol{\beta}$ and γ, which characterize the payoff function, and the parameters describing the distribution of the market-level effect, μ and σ. Parameter estimates are obtained by maximizing equation 5.2 using a Nelder-Meade optimization algorithm. Starting values for the optimization routine are found by performing a grid search over the parameter space.

[24]Explicitly solving for the equilibrium may be computationally burdensome for more complex models than the one considered here. Alternatives to using a nested fixed-point algorithm have been suggested by Ahn and Manski (1993) for a binary choice model under uncertainty and by Aguirregabiria and Mira (2002) for a dynamic discrete game of imperfect information. These approaches rely on initial non-parametric estimates of the respective expectations and equilibrium choice probabilities to then derive players' optimal decisions and draw inference on underlying preferences parametrically.

5.2 Empirical Results

As discussed in section 2.3, in the absence of data to determine the number of video retailers that may consider entry into any given market, I investigate the robustness of the estimation results to two assumptions about the size of the potential entrant pool. The alternative measures consist of an example of a large potential entrant pool, fixed at 50 firms for each of the markets, and an example of a potential entrant pool that is, for most markets, significantly smaller by setting F equal to twice the actually observed number of entrants in each market. The estimated parameters under these alternative measures for the size of the potential entrant pool are displayed in table 5.

The impact of changing the size of the potential entrant pool is most pronounced in the estimate of the mean of the market-level effect, μ. The two specifications are such that in the case of a 50-firm potential entrant pool, for most markets a smaller fraction of firms decides to enter than in the case of a potential entrant pool that is fixed at twice the number of actual entrants. The model explains this small fraction of entrants as due to a lack of attractive demographic characteristics. Consequently, the mean unobserved market-level effect has to be lower if we observe fewer firms entering the market than in the case where a large fraction of potential entrants enters. This results in a significantly lower estimate for μ in the case of the 50-firm potential entrant pool relative to the pool size set to twice the actual number of entrants.

The location-specific component of payoffs varies, in contrast to ξ, only with the actual number of entrants, $\widehat{E}$, rather than F. The estimates of the parameters that determine these location-specific payoffs are very similar across the two specifications. Most of the parameter estimates are statistically significant at traditional levels and of the anticipated sign. Table 5 also contains estimated marginal effects for the exogenous demographic variables. The marginal effects are computed by numerically differentiating the location-choice probabilities with respect to each demographic variable. The percent response in probabilities to a one-percent increase in each demographic variable above its observed average across all locations in the data set is computed on a location-by-location basis. The reported marginal effects represent the average response in probabilities across markets and locations.[25]

Population has a large and positive effect on payoffs, but this effect decreases significantly with distance. A one-percent increase in the location's own population implies, for example, approximately a three-percent increase in the likelihood of choosing this location. In contrast, a one-percent increase in the most distant population in the market area increases the likelihood of choosing the location by only one to two percent. Business density has a negative effect on firm profitability, while average per capita income has the expected positive effect on profitability, both in the location itself as well as in the remainder of the market. As with population, however, primarily income levels in the chosen location and in immediately neighboring locations where the store's customers are likely to reside have practical significance for profitability. Per-capita income levels in the most distant locations have marginal effects on the likelihood of choosing a location of approximately 0.9%, about half of the marginal effect of average per-capita income levels in the chosen location and neighboring locations in the first distance band.

As expected, the presence of competitors has a negative effect on payoffs. This effect decreases significantly, however, with distance. For example, the presence of an additional competitor within half a mile from a firm's location has a payoff effect that is approximately 70% stronger than the effect of an additional competitor within one half to three miles who in turn would have a 52 to 66% stronger effect than a competitor located more than 3 miles away in the market. Thus, incentives for firms to differentiate are strong: spatial differentiation can effectively shield one's profit from a large number of the rivals operating in the same market.

Figure 5 depicts the distribution of prediction errors based on the parameter estimates displayed

[25] Marginal effects cannot be computed for the endogenously determined expected number of competitors in the chosen location and in surrounding locations.

in the fourth column of table 5. The mode of the distribution is slightly below zero. This skewed distribution is due to the fact that the Logit functional form assumption results in strictly positive probabilities for all location choices, even though many locations are ex-post not chosen by any firm. At the extreme, we observe some prediction errors that are rather large. On average, however, the included demographic characteristics and competitive effects predict location patterns fairly well.

Similarly, figure 6 shows the empirical distribution of the market-level effects for a 50-firm potential entrant pool, as implied by the equilibrium condition that the predicted number of entrants equal the actual number of entrants in each of the markets. Figure 6 compares these standardized market-level effects to the assumed normal distribution for ξ. While the empirical distribution puts more weight on the center than the theoretical distribution, it approximates a bell curve.

5.3 Illustration of Results

The results from the market-level model of entry presented above imply that for this sample of medium-sized video markets, per-firm entry thresholds are not affected differentially by the number of competitors a firm faces in the market. The estimated parameters of the location-choice model suggest further that at the level of the neighborhood, the competitive interaction between firms is strong. Thus while competition may be intense locally, firms exploit the geographic dispersion in their demand to lessen the competitive interaction with more distant rivals.

To quantify the importance of product characteristic choices in the entry process, it is necessary to measure empirically the extent of the product characteristic space. In the case of physical location in clearly delimited markets, the size and boundaries of the characteristic space are well-defined, consisting of the area that the city covers. For other forms of product differentiation, the maximum degree to which firms can differentiate and how consumers are distributed across the various product types is not as easily observable. Because of these advantages of spatial differentiation, the setting lends itself to performing counterfactual analyses of the importance of individual features of the product-type space, such as its area and the distribution of consumers within the space, on market structure.

I perform one such counterfactual exercise by considering the role of the overall size of the characteristic space, here simply the geographic dispersion of demand, in affecting entry into the market. Other exercises of interest might include an investigation of the effect on entry of governmental regulation that restricts the extent of product differentiation between firms. In the context of spatial differentiation, such regulation most commonly takes the form of zoning ordinances that limit firms' abilities to locate freely within the entire area of a city. Similar examples from other contexts include licensing or minimum safety standards.

To isolate the effect of the extent of spatial dispersion in demand on market structure, one needs to recognize that as a city grows in size, not only does the city spread out spatially, but its population increases as well. Simply comparing predicted entry patterns across the sample markets that vary significantly in size thus does not allow us to separate the effect of the increased scope for spatial differentiation from the effect of the overall increase and scatter in population and thus market demand. To separate the contribution of each of these factors on the number of entrants that a market can support, I compare entry under two city growth scenarios.

The first scenario allows a city to grow in population only, holding its geographic layout fixed. Firms are thus still able to differentiate spatially, however, their scope for spatial differentiation does not change since the total area of the city does not grow in proportion to the population. To do so, I take one of the smallest sample cities, Jamestown, NY, with twelve Census tract locations, and artificially increase Jamestown's population in increments of 1,500 people. The growth process leaves the number of locations, their lay-out, and the relative population shares across locations unchanged. As the population rises, it is thus only the population density in the twelve locations that increases, leaving the area that the city occupies unchanged.

Predicted entry under this city expansion path is then contrasted with entry that would occur were the city to grow both in population and area. While it is difficult to simulate how Jamestown, NY specifically would expand if it grew along both of these dimensions, the cross-section of sample markets can be used as a proxy for this growth path. The sample markets are suitable for this purpose since they span a range of market sizes from Jamestown, NY at the lower end with a population of 52,583 to larger markets such as Fort Collins, CO, with a population 178,070. Furthermore, the larger cities in the sample naturally cover larger area than the smaller cities, and can thus serve to represent how Jamestown may look like were it to grow in population to their level.

Based on the estimated parameters for the 50-firm potential entrant pool, I compute the expected number of entrants for the two city-growth scenarios. To do so, I integrate over the numerical distribution of the market-level effect ξ and find predicted location probabilities and entrants that are consistent with the market-level effect, the actual number of entrants into the market, and the market's exogenous characteristics. To abstract from cross-market and cross-location variations in business density and per-capita income that could drive entry patterns, I set these variables equal to the business density and per-capita income in Jamestown for all locations in the data.

Two opposing effects drive entry into a market when the spatial dimension of city growth is removed. The first effect comes from intensified competition. If the market area does not grow with a city's population, firms cannot spread out in space any further, decreasing the incentive for additional entry. The second, countervailing effect arises due to the fact that population becomes more dense within the given market area and firms will find a larger number of consumers in the immediate neighborhood of their store. The increased access to nearby consumers thus increases the incentive for additional entry into the growing city relative to a city that grows in both population and space. The net effect of these two forces determines whether entry into a city with a fixed market area exceeds or falls short of entry that we observe in markets that naturally grow in population and area.

Figure 7 illustrates the role of geographic dispersion on expected entry as cities grow in population. In both panels, the scattered points correspond to predicted entry into the actual sample markets. The solid line represents the growth path of average predicted entry into the expanding Jamestown market, while the dotted lines denote the corresponding 95% confidence bands for entry.[26]

To separate the competition and demand effects of city growth, the top panel displays entry predictions assuming that the impact of population on payoffs does not vary by distance band. In particular, I set the three population parameters equal to the estimated parameter on population in the 0.5-to-3-mile distance band. As a city grows, the additional population then has the same impact on payoffs, regardless of where the population is located within the market. The chart demonstrates the effect of increasing a market's geographic space on firms' ability to capture localized market power by spatial differentiation. By the time Jamestown has grown in population to 150,000, allowing firms to also scatter in space amounts to an increase in the expected number of entrants of approximately ten stores. The difference between the two paths of expected entrants thus represents the contribution that the increased scope for spatial differentiation among firms makes to the number of firms that can profitably co-exist in growing markets.

Once one recognizes, however, that, as a city grows in space, customers at one end of the city are less likely to frequent a store at the other end of the city, the importance of the additional scope for differentiation decreases. The lower panel of figure 7 shows entry predictions that take both the population and competition effects into account. The estimated parameters for the entry and location choice model imply a localized pattern to the role of population in driving payoffs. The population in the immediate neighborhood of a firm's location has a higher payoff effect than

[26]The confidence bands are derived using bootstrap methods by predicting entry under 500 draws from the estimated parameter distribution for the 50-firm potential entrant pool.

the population in the remaining two, more distant, bands. The implication of this pattern on entry is that once the spatial aspect of city growth is removed, increased access to population in the immediate neighborhood increases pay offs, but this contribution falls short of the effect of increased competitive intensity on payoffs. As a result, predicted entry into the sample markets exceeds predicted entry into the growing Jamestown market with a fixed area, on average. The competition effect thus dominates. On net, however, allowing the area of the city to increase with its population does not lead to very significant increases in the predicted number of entrants; most of the predicted entry values for the actual sample markets fall within the 95% confidence band of predicted entry under the fixed market area. The results thus indicate that the absolute size of the market area has only limited implications for payoffs and consequently entry, probably since video retailing is an example of an industry where consumers' willingness to travel a long distance to a video store is low and demand is very local.

6 Discussion and Conclusion

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 product-type choices thus involve uncertainty regarding the intensity of post-entry competition and payoffs.

Competition is treated as a spill-over from firm agglomeration, the exact magnitude of which is uncertain. Firms endogenously sort into different locations within a market area depending on their expectation of the intensity of competition produced by rivals' simultaneous choices. This modeling approach resembles equilibrium models of social interaction that incorporate neighborhood effects into an agent's payoff or utility function.[27] The endogenous sorting model studied here is a small sample counterpart to these population-based models where the equilibrium represents, rather than the aggregate share of the population, a rival's likelihood of choosing a given location.

Modeling entry using an incomplete information framework entails some significant differences, compared to a game of complete information, in the characterization of the equilibrium. In a perfect information model, a given firm distribution across locations constitutes an equilibrium if each firm maximizes profits and none of the competitors has an incentive to deviate after having made its location choice. To confirm that a given firm configuration is an equilibrium thus entails verifying that the specific configuration is more profitable for each and every firm than any other possible configuration. Computing an equilibrium configuration in such a model is difficult for markets with large numbers of locations and firms. In contrast, equilibrium location choices in the incomplete information framework result from firms integrating over competitors' uncertain location strategies. Rivals' discrete actions are thereby transformed into smooth predicted location probabilities that are equal across firms in equilibrium. Due to its easily solvable equilibrium location conjectures, the Bayesian equilibrium concept greatly facilitates applying the model to a realistic, large-dimensional product-type choice set.

The conditions under which a unique equilibrium exists in discrete games of perfect information are quite restrictive (Mazzeo 2002, Reiss 1996). Numerical simulations suggest, however, that a unique equilibrium exists in the imperfect information game provided the exogenous data exhibit sufficient variation across locations. This will be true both in the case where firm clustering results in positive spill-overs to each firm's payoff and, under significantly weaker restrictions on the data, in the case studied here where the empirical results indicate a negative payoff effect from firm clustering.

[27] For a survey of recent developments in the specification and estimation of interactions-based models, see Brock and Durlauf (2001). Examples of empirical applications of endogenous sorting models into neighborhoods include Bayer, McMillan, and Rueben (2002) and Timmins (2003).

One characteristic of the equilibrium concept presented here that is not shared by the corresponding perfect information model arises from the fact that firms are not allowed to coordinate moves when making location choices. Since such choices are instead conditioned on the expectation of rivals' moves, the model allows for ex-post regret: a firm may choose a location that, once its competitors' moves are observed, is no longer its optimal choice. As an example of a scenario with a high likelihood of ex-post regret, suppose that two firms' type realizations are such that, given their expectation of the rival's location choice, they choose to locate in the same cell. Ex-post, these strategies will be optimal only if both firms' type realizations are sufficiently large to outweigh the effect of intensified competition so that clustering continues to dominate other location strategies. Such extreme clustering in one location as an equilibrium outcome of the model is, however, unlikely in large markets with large competitor sets. Additionally, the model's allowance for possible ex-post regret corresponds better to real-world environments and decision-making by firms. This holds in particular in cases where largely unobservable or unmeasurable firm-specific capital contributes significantly to firm profitability, such as marketing and advertising activities.

In this paper, market structure is assumed to be the equilibrium outcome of firms' comparisons of the one-time post-entry payoffs from entering at a particular location to the option of not entering. While in reality, firms do not move simultaneously, the motivation behind this albeit restrictive set-up is twofold. One reason is that information on firms' sequence of moves and the market conditions at the time at which they make their moves is difficult to obtain. A second, potentially more severe drawback is that dynamic models of firm and industry evolution such as the one suggested by Ericson and Pakes (1995) are computationally complex and difficult to estimate for large markets with many product-types and many competitors. Similar to other empirical models of firm entry, the static model presented here is therefore assumed to approximate the repeated firm interaction that characterizes the evolution of an industry. Further work on empirically implementing dynamic games of firm interaction is necessary to evaluate the validity of this assumption.

The model is applied to spatial product-type choices using data from the U.S. video retail industry, an industry where location is a major source of product differentiation among firms. The empirical results indicate that firms have strong incentives to differentiate spatially. At the aggregate level, the relationship between the number of firms and market size indicates that loss in margins due to a larger number of competitors is weighed against the larger scope for differentiation in larger markets. Rivalry between firms decreases significantly with distance providing an incentive for firms to spread away from each other. This incentive may be countered, however, by differences in demand characteristics across locations that are of equal importance in driving payoffs. City growth experiments show that firms' abilities to capture localized market power by spatial differentiation increase with the size of the product space. As the product space grows, however, population spreads out as well limiting the benefits of such spatial differentiation. Conditioning on population, expanding the product space thus induces only slightly higher entry than in the alternative scenario where a market's spatial dispersion of demand is held fixed.

Table 1: Descriptive Statistics, Markets and Locations

	151 Sample Markets		
	Mean	Minimum	Maximum
Market level			
Population, market	74,367	41,352	142,303
Population, main city	59,428	40,495	140,949
Population, all tracts in market	92,563	41,614	193,322
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	21.13	8	49
Number of store locations	18.72	7	44
Tract population	4,380	247	32,468
Area (sqmi)	10.10	0.10	181.50
Average distance (mi) 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. Demographic data is as of 1999.

Table 2: Tract-level Demographic Characteristics

	Mean	Minimum	Maximum
Demographic characteristics			
Population	4,417	247	20,163
Population, within 0.5 mi of tract	4,952	247	23,676
Population, 0.5 - 3 mi of tract	42,281	0	145,499
Population, 3 - 10 mi of tract	54,817	0	169,271
Per capita income, within 0.5 mi of tract	17,807	3,484	60,347
Per capita income, 0.5 - 3 mi of tract	17,413	0	38,934
Per capita income, 3 - 10 mi of tract	19,417	0	38,452
Business characteristics			
Establishment density per square mile	177.86	0.15	5239.48

Notes:
The tract's total population is placed at the population-weighted centroid. Population within different distance bands to the tract under consideration is computed as the sum of the population in tracts for which the distance to the considered tract's centroid falls within the specified range. Demographic data is as of 1999.

Table 3: Store Location Patterns, Sample Markets

	Mean	Minimum	Maximum
Firms, market	13.68	4.00	33.00
Store clustering			
Firms, tract	0.73	0.00	9.00
Firms, within 0.5 mi of tract	0.80	0.00	10.00
Firms, within 0.5 - 3 mi of tract	6.12	0.00	27.00
Firms, within 3 - 10 mi of tract	7.94	0.00	33.00
Location patterns within city's area			
Distance to city center (mi)[1]	3.02	0.02	14.96

Notes:

All stores are placed at the tract's population-weighted centroid. Competitors within different distance bands to a firm's location are computed as the number of firms in tracts for which the distance to the firm's tract falls in the specified range.

[1] The city center is taken to be the population-weighted centroid of the market's main city.

Table 4: Parameter Estimates, Perfect Information
Ordered Probit Model

	Coefficient	Std. Error	Markets in Category	
Population (α_1)	2.6362	1.0174		
Per-Capita Income	1.3109	0.5322		
Business Density	0.3746	2.0009		
γ	-2.4977	1.0478		
α_2	-0.1978	0.8667	$n = 7$	7
α_3	-0.3990	0.9494	$n = 8$	18
α_4	-0.7395	1.0121	$n = 9$	16
α_5	-0.4690	0.9330	$n = 10 - 11$	19
α_6	-0.4801	0.9782	$n = 12 - 13$	29
α_7	-0.7405	1.1829	$n = 14 - 17$	26
α_8	-0.7742	1.5380	$n \geq 18$	21
Log-likelihood	-278.49			

Firms	Entry Threshold	Per Firm Entry Threshold (s_n)	Entry Threshold Ratios (s_n/s_{n-1})
$n = 6$	46.4452	7.7409	
$n = 7$	48.3358	6.9051	0.8920
$n = 8$	52.6614	6.5827	0.9533
$n = 9$	63.1288	7.0143	1.0656
$n = 10 - 11$	72.2361	6.8600	0.9780
$n = 12 - 13$	84.7502	6.8457	0.9979
$n = 14 - 17$	115.6565	7.3902	1.0795
$n \geq 18$	186.9205	8.6258	1.1672

Notes:
Results based on 1999 demographic and firm data. Enty thresholds are expressed in thousands of people. The likelihood ratio test statistic for $s_6 = s_7 = s_8 = s_9 = s_{10-11} = s_{12-13} = s_{14-17} = s_{\geq 18}$ equals 22.32, distributed $\chi^2(7)$.

Table 5: Parameter Estimates, Entry and Location Choice Model

	Potential Entrant Pool =			
	2 x Total Entrants		50 Firms	
Variable	Coefficient (Std. Error)	Marginal Effect	Coefficient (Std. Error)	Marginal Effect
Population_0 (000)	1.8191	0.0333	2.1258	0.0393
	(0.1534)		(0.1764)	
Population_1 (000)	1.3109	0.0236	1.7349	0.0314
	(0.1200)		(0.1498)	
Population_2 (000)	0.6070	0.0121	1.1348	0.0227
	(0.1192)		(0.1486)	
Business density	-0.8077	-0.0155	-0.8889	-0.0173
	(0.1458)		(0.1477)	
Avg. Per-Capita Income_0 (0000)	0.9309	0.0180	1.0380	0.0204
	(0.1136)		(0.1233)	
Avg. Per-Capita Income_1 (0000)	1.0081	0.0193	0.9188	0.0178
	(0.2081)		(0.2043)	
Avg. Per-Capita Income_2 (0000)	0.4851	0.0092	0.4884	0.0094
	(0.2512)		(0.2601)	
γ_0	-3.4520		-3.3853	
	(0.3111)		(0.3266)	
γ_1	-1.0103		-1.0087	
	(0.0745)		(0.0923)	
γ_2	-0.3448		-0.4870	
	(0.0738)		(0.0934)	
σ	3.5829		4.6760	
	(0.3110)		(0.4316)	
μ	-2.8764		-7.0364	
	(1.3425)		(1.5801)	

Notes:
Results based on 1999 demographic and firm data. Subscript 0 denotes the immediately adjacent locations to the chosen tract, within 0.5 miles in distance; subscript 1 denotes tracts at 0.5 to 3 miles in distance from the chosen tract; and subscript 2 denotes tracts at more than 3 miles distance from the chosen tract. Tract-level business density is defined as the number of establishments (0000) per square mile. γ denotes competitive effects, and σ and μ the estimates of the parameters of the distribution of ξ.

Figure 1: Joint Entry and Location Choice Decision Tree

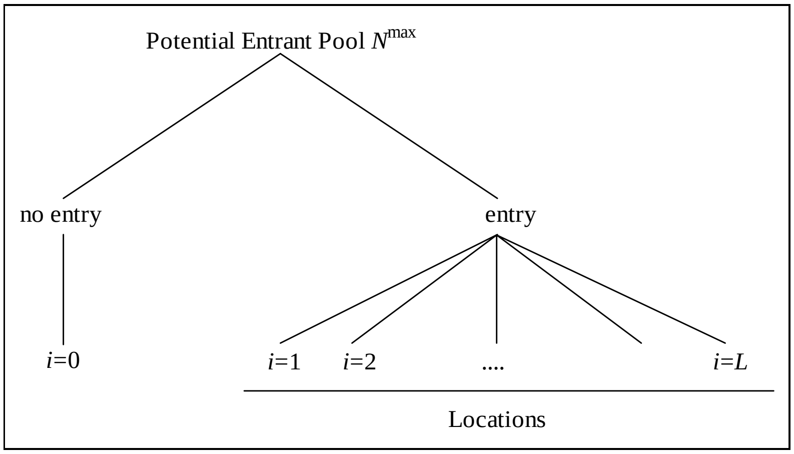


Figure 2: Illustration of Census Tract Irregularities - Wilmington, NC

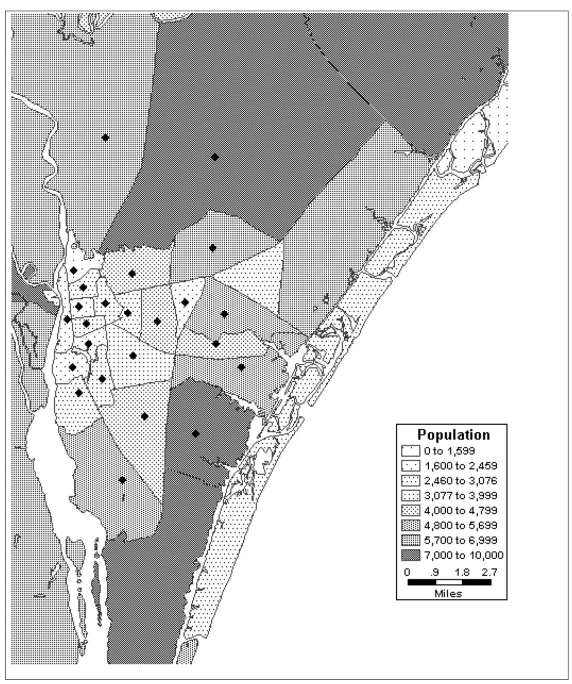


Figure 3: Impact on Profits of Competitors' Locations: Illustration

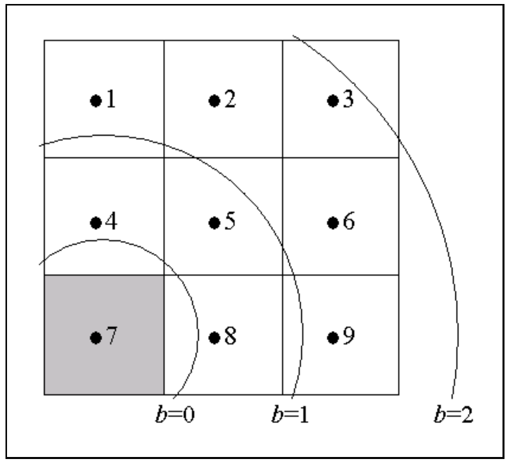


Figure 4: Sample Market - Great Falls, MT

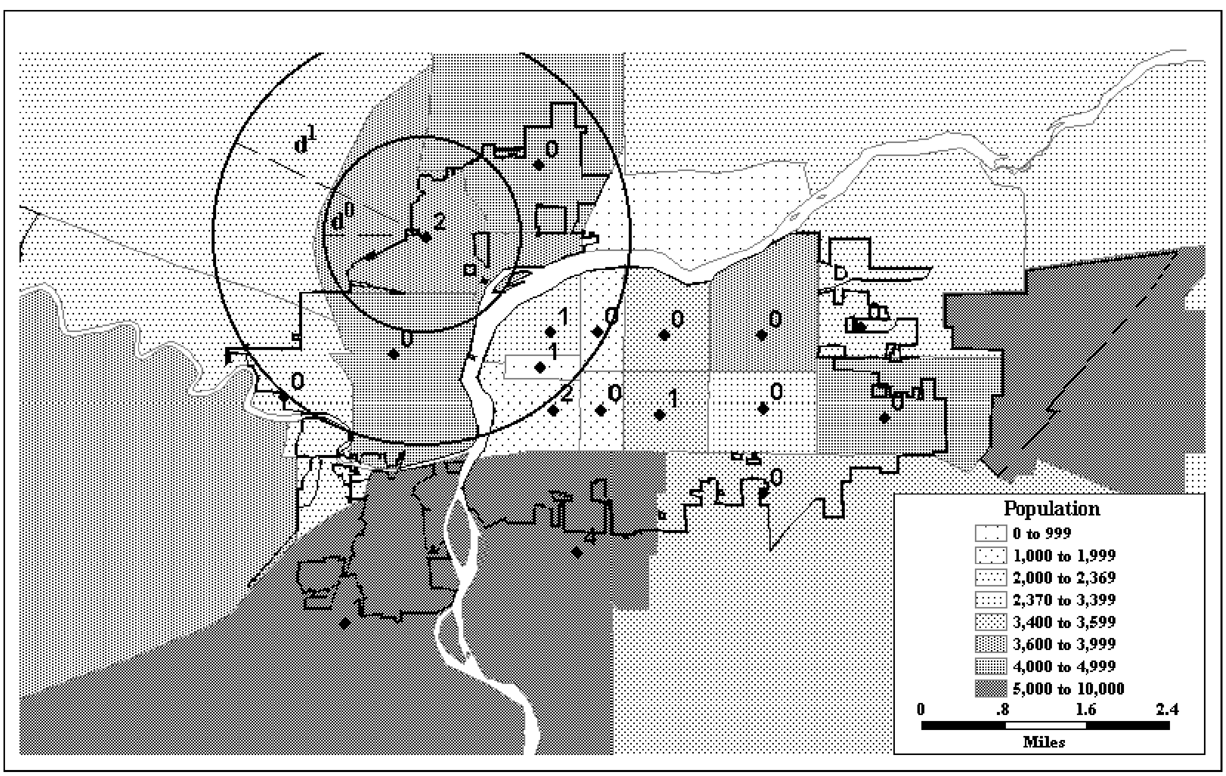


Figure 5: Distribution of Prediction Errors, Location Choice Probabilities

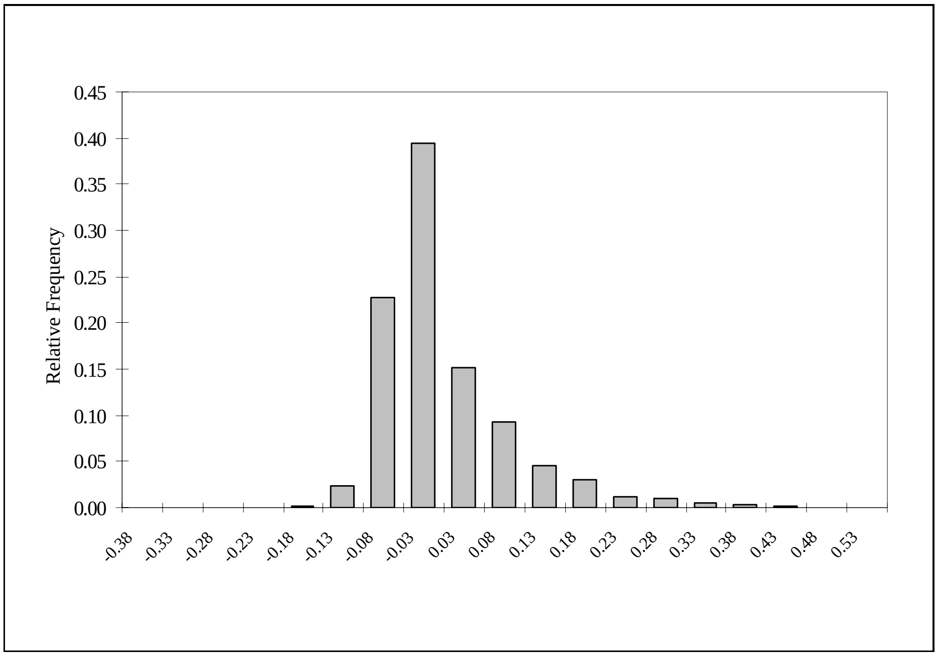


Figure 6: Distribution of Market-Level Effects

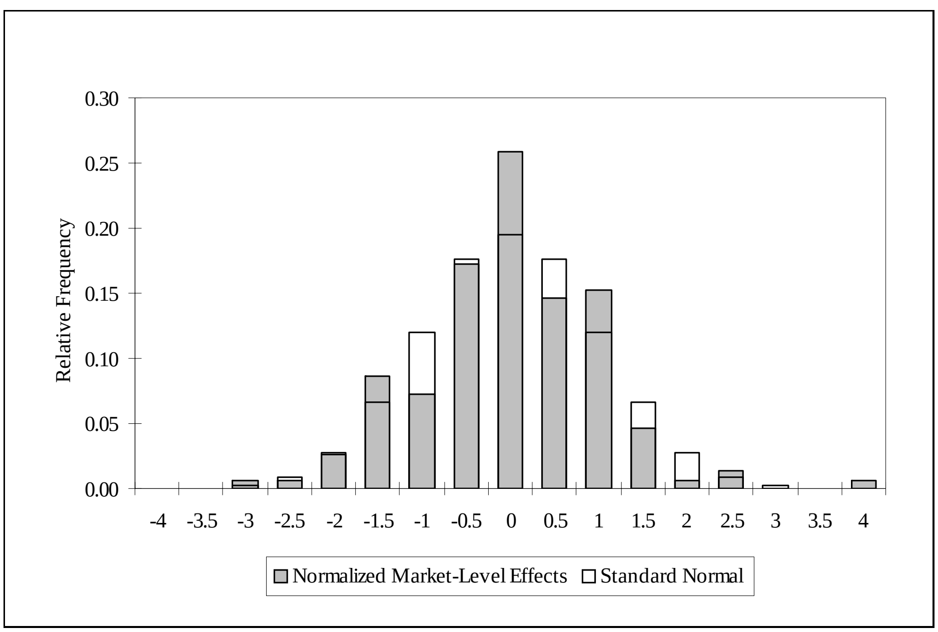
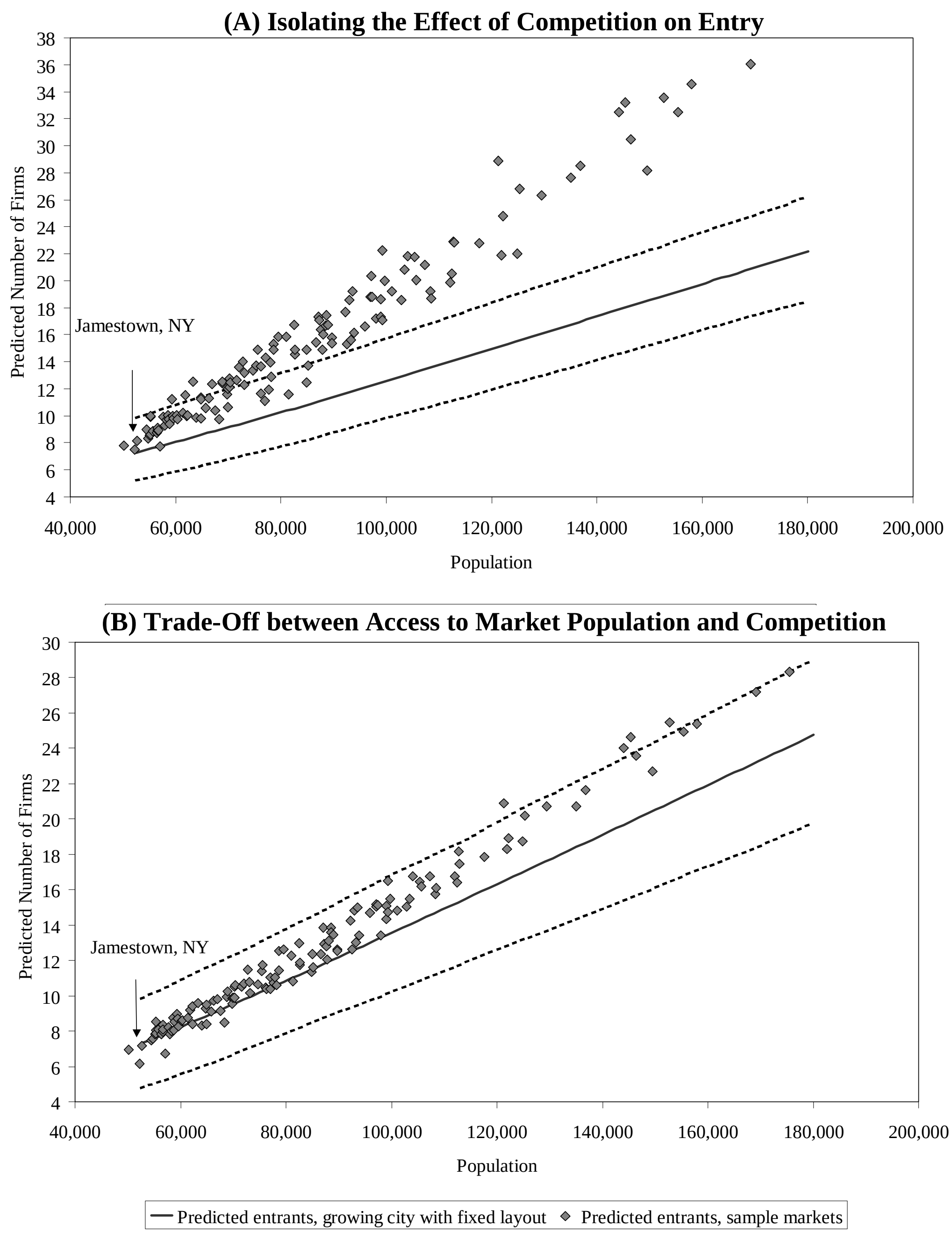


Figure 7: The Role of Spatial Dispersion on Entry



Note: Predicted entry patterns are based on estimated parameters for the 50-firm potential entrant pool. To isolate the effect of competition on entry in panel (A), all population parameters are set to the estimated effect on pay-off of population within 0.5 to 3 miles from the location.

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