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The role of captive consumers in retailers' location choices

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Abstract

This paper investigates empirically the effect of anticipated price competition and distribution costs in firms' location choices within an oligopolistic market. I set up a static location-price game of incomplete information in which retailers choose their locations based on (firm-)location-specific characteristics, the expected market power and the expected degree of price competition. In particular, I tie the firms' strategic location incentives to the population distribution using the concept of captive consumers. This approach is in line with theoretical spatial price competition models and does not require price or quantity data. I address the computational difficulties of the estimation using mathematical programming with equilibrium constraints. Applied to the supermarket industry, the model confirms the existence of benefits of spatial differentiation for firms' profits and provides evidence that firms anticipate price competition and distribution costs in their site selections.

Keywords: spatial competition, location choice, price competition, retail competition, discrete games, constrained optimization.

JEL classification: L13, L20, D43, R12, C51.

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1 Introduction

The grocery retail industry, as the endpoint in the food distribution chain, constitutes a large fraction of the US economy, with supermarkets and their major chains comprising the largest segment. The spatial nature of competition across supermarkets and potential cost advantages from an efficient supply chain management leave scope for retailers to benefit from market power, and constitute an interesting industry regarding the study of the strategic location decision of retail stores under price competition within a spatially differentiated market. This paper seeks to analyze empirically whether - in line with theoretical spatial competition models - firms anticipate price competition and distribution costs in their location decisions and, in particular, how the population distribution within a market determines the firms' location incentives. However, existing empirical entry or location models are usually based on quantity competition, and this approach misses important features when applied to markets where price competition is more reasonable. I therefore propose an alternative econometric model based on price competition and provide an application to study the location choice of the two largest retail grocery companies in the US, namely Kroger and Safeway.

To be precise, I propose a static discrete-choice location model under incomplete information whereby two firms compete in locations and prices within local duopolistic markets. The model is formalized as a simultaneous-move location game. Since in many cases we observe only the final location decision of the firms, without price or quantity data, I exploit the information inherent in location data in a reduced-form profit function using geospatial analysis. In particular, I propose the percentage of 'captive consumers' in the firm's trade area as a new empirical measure of market power under spatial differentiation. By the notion of 'captive', I refer to consumers who have access to one firm but traveling to another firm is not feasible, regardless of the price. This is a concept from theoretical spatial competition models which, to the best of my knowledge, has so far not received any explicit attention in econometric models. In a similar manner, I use the difference in 'captive consumers' between rivals as a proxy for the degree of price-competition between firms. The latter allows us to identify whether firms anticipate price competition in order to attract consumers in overlapping market areas. Additionally, the model accounts for cost aspects, in terms of the proximity of a store to the firm's distribution center, which on the one hand serves for the model identification, and on the other hand allows us to estimate the effect of endogenized fixed distribution costs in the location choice. For the estimation, I use a maximum likelihood approach and address the computational difficulties of the game-theoretic setting through the reformulation of the optimization problem as a mathematical program with equilibrium constraints (MPEC), as suggested by Su and Judd (2012).

I apply the econometric model to study the strategic location determinants for the su-

permarket industry. To be precise, I use point of interest (POI) data for traditional supermarket stores as a novel type of freely available dataset and process the data with the Geographic Information System tool ArcGIS. I find that, on average, 13% of the firm's trade area comprises captive consumers. The location model identifies an incentive for generating local market power through spatial differentiation and firms anticipating price competition as well as distribution costs when choosing a location for their stores. Leaving other rivals unconsidered, I find that the second effect of a change in captive consumers, denoted as a price-competition effect, only has a negative profit effect if the percentage of captive consumers in the firm's trade area is small enough ($<60\%$). However, considering the market presence of rivals of a larger format weakens the monopoly power of the firms, and I find a clear negative price competition effect that becomes stronger as the competitive region becomes relatively more important for the firm.

The main contribution of the paper is the explicit consideration of strategic aspects of price competition in a spatial competition model based on observed location data. In particular, I tie the firms' strategic behavior to the population distribution, which has been discussed by Davis (2006) as long recognized as an important link in order to evaluate any policy interest.

The literature on competition models without price and quantity data goes back to Bresnahan and Reiss (1990), who use the fact that under quantity competition à la Cournot, the reduced profit function can be expressed in terms of the number of firms in a market. A latent profit specification is used to estimate a discrete-choice market-entry model. Katja Seim (2006) extended the model to an entry-location game where firms additionally choose their locations within a market. In her approach, the 'measure of competition' is the effect of an additional firm in a certain concentric ring (a 'donut') around the store location, i.e., the corresponding location incentive is independent of the population distribution. In recent years, her model has been extended to differentiation in more than one dimension (Datta and Sudhir, 2013) or else allowing for asymmetries in competitive interaction (Zhu and Singh, 2009). However, applying these models to industries where price competition seems more reasonable (e.g., supermarkets), the implicit assumption of quantity competition or a fixed exogenous market price does not allow us to identify the appropriate location incentives. The two crucial limitations of this kind of 'donut-model' are the following: First, the strong assumption that a rival locating within a certain distance (ring) of the firm has a 'ring-uniform-competition effect' disregards the population distribution within a 'distance ring'. In other words, considering two potential locations of the rival which are at the same distance from the firm but which differ in terms of the associated population density, this paper assumes that a rival locating at a sparsely populated location exercises the same competitive pressure on the firm as if it were located at the densely populated location. Second, the model can only estimate the 'net effect' of competition but not the incentives that lead to the observed market structure. While the

latter is also discussed in Datta and Sudhir (2011), stating that these structural models are "incapable of separating the 'net effect' of competitors into a volume effect and a price competition effect", in their proposed solution and by additionally using revenue and price data, they rely again upon the critical assumption of a ring-uniform-competition effect. My model offers a way of determining strategic incentives of price competition without additional data while at the same time getting rid of the 'ring-uniform-competition effect' assumption. Incorporating the effect of the population distribution within a trade area, this approach builds on implicit distances instead of accounting for the distance to the competitor straight away in the profit function. Since I focus on the interplay between the population distribution within a market and the price competition strategies that firms adopt after choosing the location, I refrain from modeling how the market structure arises. Instead, for simplicity and with a view to the application, I condition the analysis on duopoly markets with each firm operating one store.

Methodologically, the paper contributes to the application of recently developed computational methods for the estimation of structural models. So far, the MPEC approach has been shown to be applicable to the structural estimation of dynamic discrete choice models (Su and Judd, 2012), BLP demand estimation (Fox and Su, 2012) as well as the estimation of static games (Su, 2012). While Vitorino (2012) provides the first application of the MPEC approach to an empirical, static, binary choice model of market entry, this paper provides an application to a multinomial location choice model.

The paper is organized as follows. First, the reader is introduced to some key elements of price competition under spatial differentiation (theory) which will be used in the model. Second, I set up the econometric location model and subsequently explain the estimation method and computational strategy. Finally, I present the data used for the application and report the results. The paper finishes with a comparison of the main findings with alternative approaches in the literature and comments on possible extensions of my framework.

2 Economic intuition

To get an economic intuition about the strategic price setting behavior of two spatially differentiated retailers, let us make use of the Hotelling (1929) framework, the workhorse of theoretical spatial analysis, to highlight some key aspects and to identify the observable strategic elements of price competition in space that will be considered later in the empirical model.

Consider two firms, A and B, located at the extremes of a linear market. Consumers are uniformly distributed over the line. Additionally, at each extreme, where the firms are

located, there lives a consumer mass X_A and X_B respectively. Consumers have a unit demand, face displacement costs and decide at which firm to buy, maximizing their utility. In addition to this textbook framework, consumers face an exogenous restriction on the travel distance (D_{max}) which reflects their time constraint for shopping.

Figure 1 sketches this toy model. If D_{max} is large enough, the market area between the two firms can be partitioned into a 'captive area of firm A', a 'competition area' and a 'captive area of firm B'. In the following, the notion 'captive' refers to areas where consumers only have access to one firm since the cost of displacement to another firm is too high given their time constraint on shopping. The demand of firm A is given as the sum of those consumers that the firm draws from the competitive region and the firm's captive consumers. Since the firms cannot identify which region the consumers come from when visiting the store, and since the consumers have a unit demand, the firms have to set uniform prices. Solving the simultaneous profit maximization problem, the measure of captive consumers of a firm plays an ambiguous role. An increase in captive consumers causes an increase in the equilibrium price of the firm, which reflects the market power effect. However, since consumers in the competitive area are rational, buying from the firm that minimizes the overall cost in terms of price and transportation disutility, an increase in the difference of captive consumers with respect to the rival decreases the demand drawn from the competitive area. Thus, for a given number of captive consumers of firm B, an exogenous increase in the number of captive consumers of firm A induces the firm to exercise this market power in setting a higher price, but the positive effect on revenues is mitigated through a decrease in the number of consumers drawn from the overlapping market area where competition takes place.

Since the purpose of this toy model is to tell a story of price competition in space, I briefly summarize the main insights here (Appendix A gives an outline of the maths.)

1. An increase in the number of captive consumers of A increases the firm's price-setting power.

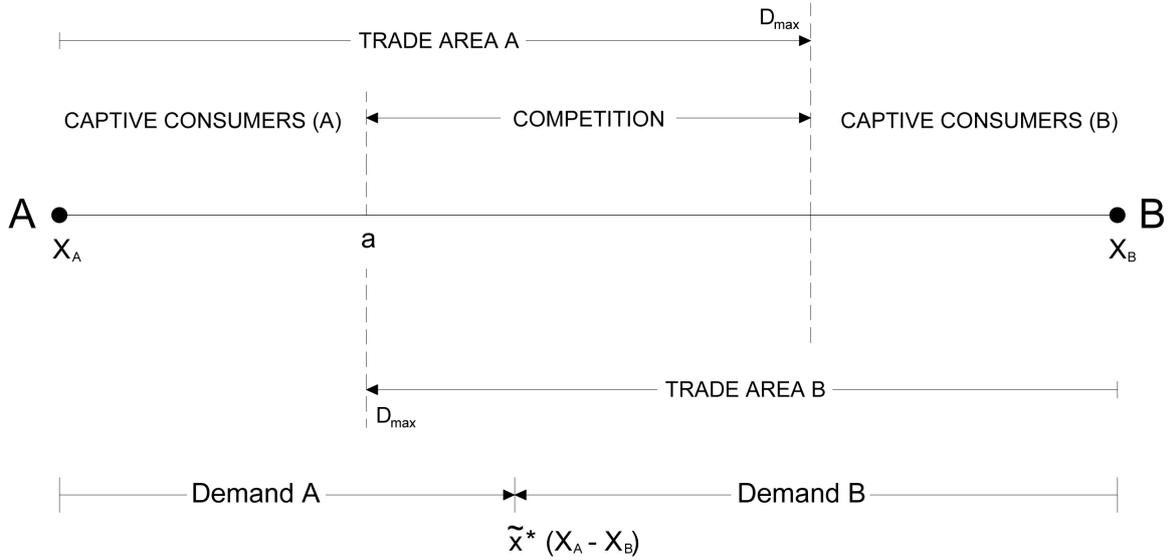
This profit-enhancing effect of captive consumers is mitigated through a negative quantity effect on the demand from the competitive area.

2. If the difference in the number of captive consumers between the firms (normalized by the consumers in the competitive area) is small enough, in equilibrium both firms can draw demand from the competitive region.

However, if the reservation value of the consumers is high enough, there exists a critical percentage of captive consumers in the trade area such that, for a higher fraction of captive consumers, the firm is better-off restricting the demand to the captive area, setting the monopoly price.

3. If the number of captive consumers of A is sufficiently high with respect to the

Figure 1: Stylized price setting under spatial differentiation and fixed trade areas.



captive consumers of B, an increase in the number of captive consumers of A reduces the revenues that firm A draws from the competitive area (operating in the elastic section of the demand curve from the competitive area).

An increase in the number of captive consumers of A always increases the total revenues of the firm.

In the following, Section I transfers this idea to a real geography, discrete, location-price game, assuming firms to anticipate the role of captive consumers when choosing from a finite number of locations to maximize their profits.

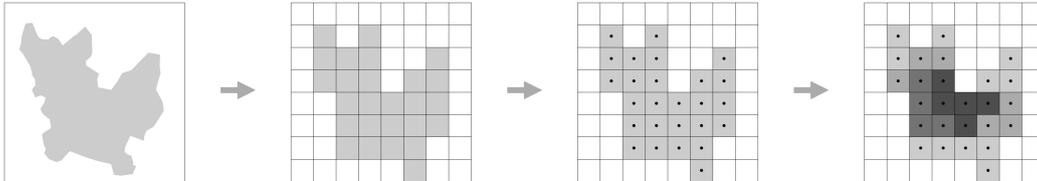
3 An econometric spatial location-price game

Analyzing firms optimal location choices empirically, it would be ideal to have access to prices and sales data at the firm level to model the demand side (e.g., Davis, 2006). Unfortunately, these firm-specific data are generally not available, whether for the researcher, the rival firm or any third party (e.g., anti-trust organizations, local government). Inspired by Seim's (2006) seminal work, I provide a model that exploits the information inherent in the observed location decision of the firms, but set up the model in such a way that I fully exploit the population distribution within the market in order to reveal the firms' location incentives.

3.1 The model

Consider a spatial market m of any polynomial shape with a finite number of equally-spaced discrete locations L_m and a corresponding discrete consumer distribution $F_m(X)$, as illustrated in Figure 2.

Figure 2: Discrete locations in a polynomial market.



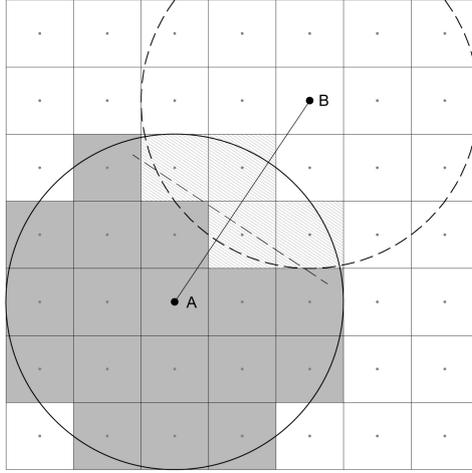
There are two firms with one store each in the market, and each firm faces a discrete choice problem to identify the optimal location which maximizes its profit, anticipating the subsequent price competition with the other firm. Assume further that consumers buy from the store for which the price plus the travel cost is the lowest, and let them face a maximum exogenous travel distance (radius D_{max}) which determines the potential trade area of a firm.¹ Assuming that the market within the range of the stores is covered, i.e. all consumers buy from either of the two firms, we can distinguish three scenarios: both firms located at the same location (Bertrand competition), differentiation with an overlapping range of influence of the stores (differentiation with captive consumers), and the case of captive consumers only (full monopolization). Figure 3 illustrates the most interesting case of differentiation with captive consumers.

The light gray area depicts the overlapping market range, denoted as the 'area of competition', and the dark gray area illustrates the 'captive consumers' of firm A. The dashed line depicts the analog to the indifferent consumer in the linear model, depending upon the price setting of the firms. While the total potential demand of a store is the sum of consumers in the distance ring around the store location, the realized demand of A is only those consumers below the dashed line.

Hence, in the simplest framework, the optimal location choice for the store is determined through the potential demand, the market power in terms of the share of captive consumers and the strength (or dominance) of price competition in the competitive region. The intuition for the economic mechanism follows the example from the previous subsection. A higher fraction of captive consumers increases the price-setting power and hence the profit per unit sold. However, for a given number of captive consumers of the rival, an

¹Defining an exogenous cap on the shopping distance is standard in the empirical literature, e.g., Seim (2006), Datta and Sudhir (2013), Holmes (2011).

Figure 3: Price competition and market power in space.



increase in captive consumers increases the price difference with respect to the rival which shifts the position of the indifferent consumer towards the location of the rival firm, and thus decreases the demand drawn from the competitive region. Hence, I expect to find a positive market-power effect of captive consumers but a negative-quantity effect for those revenues drawn from the competitive area. However, whether this logic is reflected in the firms' behavior is an empirical question.

For the econometric specification of a firm's profit function I follow a reduced-form approach. In order to differentiate between the two effects of captive consumers, I use two different strategic variables, the absolute number of captive consumers and the difference with respect to the rival. In the simplest sense, the profit function of a store of firm F for each location $l = \{1, 2, \dots, L_m\}$ is defined as follows: ²

$$(I) \quad \pi_{Fl}^I = \beta_1 \bar{X}_l + \beta_2 \frac{Captive_{Fl}}{\bar{X}_l} + \beta_3 \frac{\Delta Captive_{Fl}}{\bar{X}_l} + \delta Z_{Fl} + \omega_{Fl}$$

where \bar{X}_l indicates the potential population that can be reached by a store at location l and Z_{Fl} is a firm-specific cost-shifter indicating the distance from location l to the closest distribution center (DC) of firm F . The variable $Captive_{Fl}$ indicates the number of captive consumers of firm F located at l for a given location of the rival. The division by the population within the trade area turns the variable into the percentage of captive consumers within the trade area, and hence provides a measure of the market power on the interval $[0, 1]$. The variable $\Delta Captive_{Fl}$ measures the difference in captive consumers with respect to the rival as an indicator for the strength of price competition in the com-

²The model abstracts from the outside option for consumers to buy from other grocery retailers. However, in a sensitivity analysis I consider possible rivals of a larger format.

petitive area. Both variables depend upon the location structure of the market, which is the outcome of the decision of firm F locating at l given that the rival $-F$ is located at k and are therefore endogenous in the model.

Note that specification (I) assumes a constant marginal effect of the difference in captive consumers. However, it seems more reasonable to assume that the competition effect becomes more severe in the location choice as the percentage of consumers in the competitive area increases. Hence, a second specification allows for an interaction effect between the difference in the share of captive consumers and the percentage of consumers within the competitive area.

$$(II) \quad \pi_{Fl}^{II} = \pi_{Fl}^I + \beta_4 \frac{\Delta \text{Captive}_{Fl}}{\bar{X}_l} \left(1 - \frac{\text{Captive}_{Fl}}{\bar{X}_l} \right)$$

The unobservables at the firm-location level ω_{Fl} are private information of the decision-making firm, captured in the vector ω_{mF} of dimension $L_m \times 1$. The realization is neither known by the rival nor by the researcher, but it is common knowledge that, for each market, each ω_{mFl} is independently and identically distributed extreme value. Hence, considering the information structure of all agents, notice that we - as researchers - are as informed as the least informed party of the location game.

The information set of firm F when making its location decision in market m is $\mathcal{I}_m^F = (X_m, Z_m, \omega_{mF})$, with (X_m, Z_m) being common knowledge among firms and researchers and ω_{mF} being private knowledge of the firm.

Conditional upon \mathcal{I}_m^F , the firm forms its belief about the location choice of its rival and makes its location decision based on expected profits. In the following, I use for the beliefs of firm F about its rival's behavior the notation BP_m^{-F} , a $L_m \times 1$ dimensional vector of Bayesian probabilities for each possible location l . Analogously, BP_m^F denotes the beliefs of $-F$ about the location choice of firm F .

Given the profit specification detailed above, the introduced uncertainty about the rival's strategy implies forming expectations about Captive_{Fl} and $\Delta \text{Captive}_{Fl}$. Omitting again the market subscript, the expected profit of specification (I) and (II), respectively, is

$$(1) \quad \pi_{Fl}^{Ie} = \beta_1 \bar{X}_l + \beta_2 \frac{E_{BP^{-F}}[\text{Captive}_{Fl}]}{\bar{X}_l} + \beta_3 \frac{E_{BP^{-F}}[\Delta \text{Captive}_{Fl}]}{\bar{X}_l} + \delta Z_{Fl} + \omega_{Fl}$$

$$(2) \quad \pi_{Fl}^{IIe} = \pi_{Fl}^{Ie} + \beta_4 \frac{E_{BP^{-F}}[\Delta \text{Captive}_{Fl}]}{\bar{X}_l} \left(1 - \frac{E_{BP^{-F}}[\text{Captive}_{Fl}]}{\bar{X}_l} \right)$$

For the detailed calculation of the variables see Appendix B.

Note that the profit specification (1) is linear in its parameters as well as in terms of beliefs, while specification (2) is nonlinear in terms of the beliefs. Furthermore, note that while the market structure in terms of captive consumers enters directly into the profit equation of both firms, firm-specific variables like the distribution distance have only an indirect effect on the rival's profit through its beliefs.

As can be deduced from the profit equation above, for a profit maximizing firm its best response depends upon the firm's beliefs about the rival's choice probabilities. The solution concept of the location game is the Bayesian Nash equilibrium, such that the equilibrium conditions are

$$\begin{aligned} BP_l^F &= \Psi_l^F(BP^{-F}, X, Z; \beta, \delta) \quad \forall l \\ BP_l^{-F} &= \Psi_l^{-F}(BP^F, X, Z; \beta, \delta) \quad \forall l \end{aligned}$$

where Ψ_l^F is a function that defines the choice probability of location l for a store of firm F , which has to be equal to the beliefs of the rival for any possible location. The analog holds for the rival.

Given the latent profit equations (1) and (2), the choice probability for a profit-maximizing firm F of choosing location l , conditional upon there being two firms in the market, can be written as follows:

$$\Psi_l^F \equiv P(d_{Fl} = 1 | BP^{-F}, X, Z, \beta, \delta) = P(\bar{\pi}_{Fl}^e + \omega_{Fl} \geq \bar{\pi}_{F'l'}^e + \omega_{F'l'} \quad \forall l' \neq l)$$

and under the assumption of ω_{Fl} being EV type I distributed:

$$\Psi_l^F = \frac{\exp\{\bar{\pi}_{Fl}^e(BP^{-F}, X, Z; \beta, \delta)\}}{\sum_{l'=1}^L \exp\{\bar{\pi}_{F'l'}^e(BP^{-F}, X, Z; \beta, \delta)\}} \quad (2)$$

The analog holds for the rival firm $-F$.

3.2 Maximum likelihood estimation approach

The estimation of static games with incomplete information implies two main challenges. Once we have chosen an estimation approach, we have to find a way to solve the game computationally. Second, if there is a chance of multiple equilibria in the model, this has consequences for the computation as well as for the identification of the parameters that we aim to estimate based on only one observed equilibrium.

3.2.1 Computational methodologies

As outlined previously, the choice probabilities in an incomplete information game depends upon the beliefs about the rival's strategy ($\Psi^F(BP^{-F})$). This implies that the

likelihood function to be maximized depends upon the unknown Bayesian probabilities, a fixed point problem that arises from the equilibrium condition of the game and which makes an iteration on the parameters infeasible without solving at some point for the equilibrium of the game. I will briefly outline the different methodologies that have been developed to address this issue and discuss why I choose the MPEC approach for this problem.

The first computational methodology to address this issue was the nested fixed point (NFXP) algorithm developed by Rust (1987), with a suggested application to static games in Rust (1994). The algorithm solves in each iteration on the parameters for the fixed point of the game providing a full-solution approach. However, the computational burden of this methodology is not only the CPU time but, more importantly, the trouble in the presence of multiple equilibria. While, based upon an assumption about the competitive effect, Seim (2006) was able to prove the existence of a unique equilibrium for her model and successfully implement the NFXP approach; in the presented model, as in many other application, this is not the case, which implies two problems of this approach: First, if the number of equilibria is unknown, there is no way to guarantee that in each iteration all possible equilibria have been found. Second, the number of equilibria may change for different parameter sets, which can cause jumps in the likelihood function.

These complications have motivated the development of alternative maximum likelihood methodologies such as the two-step method, going back originally to the dynamic single agent model of Hotz and Miller (1993). This method is based on the idea of estimating in an initial step, non-parametrically, the Bayesian probabilities. In a second step, the estimates are used as variables for the beliefs so that the coefficients of the profit function can be estimated using a standard probit or logit model. In other words, the parameters are estimated such that the choice probability is as close as possible to the first-stage estimates. Conditioning in the second stage on the equilibrium probabilities from the first stage, which are apparently 'played by the observed data', addresses the multiplicity problem and, at the same time, implies getting rid of the fixed-point problem. However, an important requirement of this method is a consistent estimate at the first stage, which is problematic in many applications dealing with small samples and in the present model in particular, since the number of possible choices of the stores differs across markets.

Picking up the advantages of these two approaches, Aguirregabiria and Mira (2002) suggest the nested pseudo-likelihood (NPL) estimator which, analogously to the two-step method, uses an initial estimate (or guess) of choice probabilities, but after estimating the structural parameters computes new choice probabilities and goes on with the iteration on the choice probabilities until convergence is achieved, i.e., swapping the order of the

nesses of the NFXP algorithm. If the model has more than one equilibrium, the authors suggest using different starting values and choosing the outcome with the largest pseudo-likelihood. However, as discussed in Pesendorfer and Schmidt-Dengler (2010), a required assumption to achieve convergence involves stable best-response equilibria. Especially, these state that, already, a slight asymmetry in the firms' payoffs makes it difficult to verify the stability of all the possible equilibria, and this is just the case in my model inherent in the firm-specific distribution distances, implying that this approach cannot guarantee finding the equilibrium of the model. ³

For a more detailed discussion on the general pros and cons of these three methods for the estimation of discrete games, see, for example, Ellickson and Misra (2011).

In this paper, I make use of the recent advances in this field, reformulating the econometric model as a mathematical problem with equilibrium constraints (MPEC), as suggested by Su and Judd (2012).⁴ Their idea is clear and simple: constrained optimization problems are present in many economic applications (e.g., utility maximization subject to budget constraints; transportation problems, etc.), but so far, optimization problems in econometrics (regression models) have used unconstrained optimization approaches. The authors show that treating the equilibrium choice probabilities together with the structural parameters as a vector of parameters to be estimated provides a way of formulating the maximum likelihood approach as a constrained optimization problem that can be solved with any state-of-the-art nonlinear constrained optimization solver (e.g., KNITRO). Consequently, there is no need to repeatedly compute equilibria, the stability property of an equilibrium is not an issue and it is relatively easy to implement.

Implementation of the MPEC approach:

Formulating the model as a constrained optimization problem on the joint parameter space (β, δ, BP) , can be written as follows:

$$Max_{(\beta, \delta, \{BP_m^F, BP_m^{-F}\}_{m=1}^M)} \sum_{m=1}^M \sum_{l \in \mathcal{L}_m} [d_{mFl} \cdot \log(BP_{ml}^F) + d_{m-Fl} \cdot \log(BP_{ml}^{-F})]$$

s.t.

³Although in a static framework the stability concept may be considered to be different from the discussed dynamic framework, note that static games are just a special case setting the discount factor as zero. Hence, whenever the initial guess does not exactly coincide with the true equilibrium, a small perturbation is enough to make it impossible for the algorithm to reach that equilibrium if it is an unstable one.

⁴An example for a static discrete-choice game of market entry is provided by Su (2012), and a first application by Vitorino (2012).

$$\begin{aligned}
BP_{ml}^F &= \Psi_{ml}^F(BP^{-F}, X, Z; \beta, \delta) \quad \forall l, m \\
BP_{ml}^{-F} &= \Psi_{ml}^{-F}(BP^F, X, Z; \beta, \delta) \quad \forall l, m \\
0 &\leq BP_{ml}^F \leq 1 \quad \forall l, m, F
\end{aligned}$$

Note that I assume that the parameters (β, δ) are the same for all markets, but the Bayesian Nash equilibrium (BP_m^F, BP_m^{-F}) is solved separately for each market.

Given the smooth and concave likelihood function and the fact that the choice probabilities of potential locations are strictly bounded on $[0 + \epsilon, 1]$, for any parameter vector (β, δ) , the existence of an equilibrium is guaranteed by Brouwer's fixed point theorem.

To solve this optimization problem taking into account the high dimensionality of the problem, I use the KNITRO solver through MATLAB.

3.2.2 Multiple equilibria and identification

While the existence of an equilibrium is guaranteed, let us consider the potential multiplicity of equilibria. Such multiplicity can come from either the identity of the firms or the distribution of location characteristics within a market.

First, contrary to Seim's (2006) approach, in the present model I do not assume firms to be completely symmetric, so that the identity of a firm that chooses a given location matters. Both firms face an analogous problem, but the distance to the closest DC is firm-specific and so are the equilibrium choice probabilities. However, using a maximum likelihood approach for the estimation, through the maximization of the overall likelihood, these firm-specific characteristics of location serve as a kind of implicit equilibrium selection rule regarding the identity of the firms.⁵ Hence, the availability of firm-specific location characteristics becomes a necessary data requirement to deal with the multiplicity inherent in a firm's identity (Data Requirement 1).

Second, for some distributions of location-characteristics and the true parameters (β^*, δ^*) , there may be more than one local equilibrium, but I observe only one in each market. In this respect, we follow the standard assumption in the literature that for markets with the same (exogenous) observable characteristics, firms coordinate on the same equilibrium (Assumption 1). That is, I admit the possible existence of multiple equilibria but assume that there are no multiple equilibria played out in the data, such that the multiplicity issue does not hinder the identification of the equilibria.

As commented upon earlier for the NFXP approach, the multiplicity of equilibria also goes along with computational challenges, in particular those inherent in the repeated solving of the game. Using the MPEC approach, I optimize on the joint parameter space of struc-

⁵Zhu and Singh (2009) discuss the usage of firm-specific variables, like the distance to the closest DC, in another context. They set up a model with firm-specific parameters and make use of distances to firm-specific facilities as exclusion restrictions to guarantee parameter identification.

tural estimates and beliefs, solving the game only once, which overcomes the problems associated with repeatedly solving the game (for a detailed discussion, see Su (2012)). However, and analogous to other numerical optimization algorithms, this approach can only find a local optimum which does not need to coincide with the global one, such that the challenge of finding all the equilibria remains. In order to increase the probability of finding the best equilibrium in terms of the highest log-likelihood, I use many different initial values.

With respect to the identification of the parameters in the model, I exploit the variation of general location characteristics, firm-specific location attributes within markets, and the variation in the distribution of the characteristics across markets, together with the observed store locations. With respect to the strategic effects, we need the identification requirement that the markets are large enough or D_{max} small enough, such that $A_{kl} = 0$ for at least one l , $\forall k, \forall m$ (Data Requirement 2). In other words, there is no location from which a firm can serve the whole market. This is a weak requirement that prevents any collinearity problem between the strategic variables.

Furthermore, I make the strong assumption that any kind of market effects are uncorrelated with the market structure as well as the population distribution, such that non-negative profits for the firms are guaranteed. Accounting for this unobserved heterogeneity across markets is, at the moment, considered to be computationally too expensive.

3.2.3 Coherence with the theory

Considering the coherence of the estimates with the theoretical intuition outlined initially, the arguments are as follows. First, if there was no interaction between the firms, the only profit determinants would be the potential consumers within the trade area and the cost structure. Second, if firms competed for market shares and prices were exogenously given, then additionally the number of 'captive consumers' should enter positively in the profit function; yet the difference in captive consumers, as a proxy for price differences, should be irrelevant in this context. Third, if firms anticipated price competition in their location choices, a positive difference in the share of captive consumers with respect to the rival is supposed to decrease the demand drawn from the competitive region, and hence should enter with a negative sign in the profit equation.

4 Data description

In my application, I consider the location choice of the two strongest (traditional) supermarket chains in the US, Kroger and Safeway, whenever they encounter each other in a local market. This example has been chosen because, statistically, both firms seem to target the same type of geographic markets and consumers and they sell similar grocery

products. Hence, abstracting from some preferences over one or another private label which is not part of this paper, the products of the firms can be assumed to be perfect substitutes. To set up the necessary dataset for the analysis, I use four types of dataset: observed store locations, locations of DCs, spatial administrative units for the market definition, and spatial subunits (smaller than the market definition) with associated population characteristics, all of which I combine using the geographical information system ArcGIS.

First, taking advantage of the advances in consumer services for GPS users, I use POI datasets for GPS users to identify the store locations of the two firms as well as their primary rivals of a larger format, i.e., Wal-Mart and Target. The advantage of this type of data source is that locations are already geo-codified to an eight-digit latitude/longitude format and can directly be imported into the geographic information system that I use for the analysis, thereby avoiding any type of matching problems.

A second dataset identifying the locations of regional DCs is constructed using information from the firms' websites. Making use of the GIS North American Address Locator, I geo-code the street addresses of the DCs in a latitude and longitude format analogous to the store dataset.

A third type of dataset, which is provided by the GIS online library, contains borderline definitions (in polygon format) of different administrative spatial units, which I use for the market definition. Using the insights from my previous paper, where I find that 90% of all stores of the firms considered are located within urban areas (UAs), i.e., densely populated regions, I use UAs as the market definition (for a more detailed discussion, see my paper "Hotelling meets Holmes").

Finally, a fourth dataset contains all the census block groups in the US as the smallest available geographic unit for which associated population characteristics are available. This dataset is available from the US Census Bureau and is provided in a shape file format with associated demographic characteristics by GIS. By construction and in contrast with larger spatial units, the block groups capture relatively homogeneous population clusters. Furthermore, I need to know the maximum radius within which a store draws consumers (range of influence); this is taken from the Kroger Fact book, which states that its supermarkets "typically draw customers from a 2.0-2.5 mile radius." I use the upper bound, setting $D_{max} = 2.5$ miles, and assume that for Safeway its supermarkets exhibit a similar range of influence.⁶

Before combining this available information, I project each of the four datasets onto an x-y Cartesian coordinate system (Albers Equal Area Conic Projection), which builds the

⁶Note that the construction of the variables rest on the definition of the exogenous radius of influence. Since this is the case in most of the empirical spatial competition models, and since for a small perturbation of the radius I do not expect any change in the conclusions, I rely upon the information provided by Kroger and refrain from testing alternative values.

reference system for the spatial analysis. Furthermore, in this paper, I restrict the analysis to UAs which are sufficiently far from each other ('isolated') so as to guarantee that consumers patronize only those stores in the market where they have their residence.⁷ Given this database, I conduct the discretization of the locations. First, I discretize the potential store locations inside a market, defining over each market a grid of equally sized cells of 1.0x1.0 square miles, which is small enough to fulfill the identification assumption of the model, and has the advantage that the population in each cell corresponds to the population density of the associated BG, which is measured in pop/sqmi.⁸ Next, I define the centroids of the cells as possible locations. For computational reasons, I exclude markets with more than 500 potential locations. This dataset deals with a set of 70 isolated markets with both firms present; however, I center my analysis on the 31 urban markets with two competing stores, one of each firm. On average, these markets consist of 34 potential locations, with the smallest market counting 12 locations and the largest 112. Now I augment the discretized market dataset combining each location with the associated block group characteristics and the observed store locations, and I compute the Euclidean distance of each location to the closest DC of each firm and to the closest big-box store, considering Wal-Mart and Target. Figure 4a visualizes the discretized structure for three example markets, and Figure 4b the associated population distribution and observed store locations of Kroger and Safeway as dots and triangles, respectively. Note that the sales potential is not uniformly distributed within the neighborhood of the stores, which motivates my approach of constructing a strategic variable that depends upon the population distribution rather than defining a uniform radial-competition effect and accounting for the total population within the trade area only as a covariate in the profit equation.

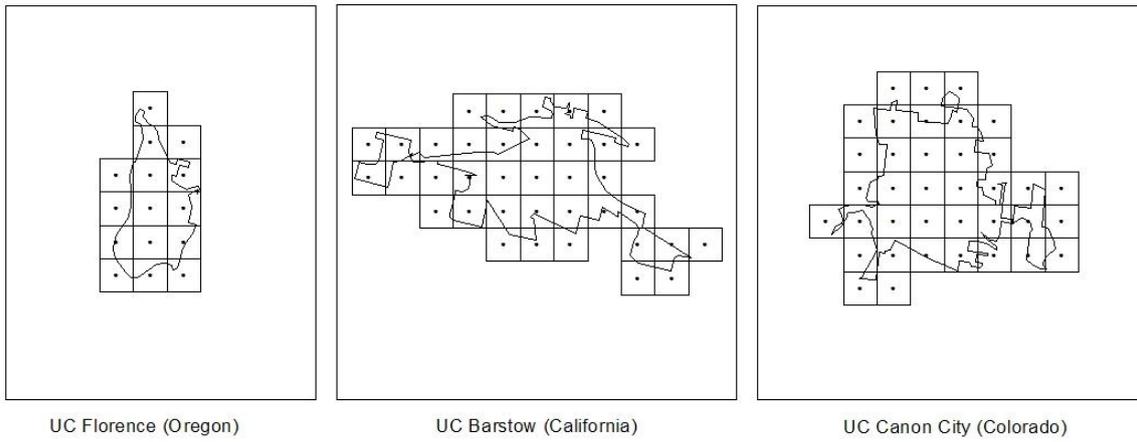
As defined by the model, the construction of the strategic variables relies upon delimited trade areas of a 2.5 miles radius. Hence, I construct a distance matrix that measures the Euclidean distance from each location to any other location within the same market, which is then used to construct the feasibility matrix A_m for each market. Figure 4c illustrates the feasibility of consumer locations for given store locations using distance rings with a radius of 2.5 miles to define the trade area.

Next, I export the dataset of discrete locations and its associated variables as well as the distance matrix to MATLAB. Table I provides the descriptive statistics of the variables of interest at the observed store locations for the set of markets with one store per firm. Considering the exogenous variables of the model, \bar{X} defines the total population within a 2.5 miles radius of the store measured in thousands. The variable Z indicates the dis-

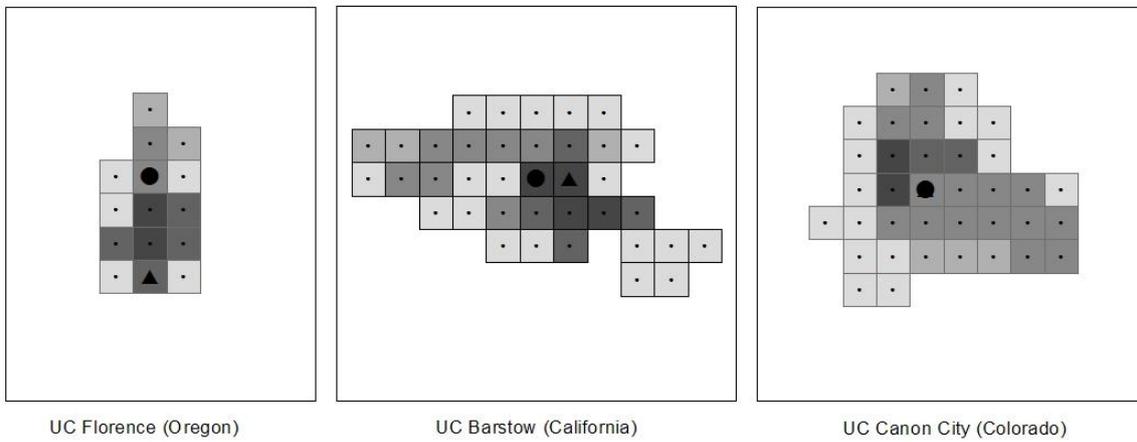
⁷By 'sufficiently far' I refer to markets for which the range of influence of each location exclusively contains locations from the market where the store has its establishment.

⁸Choosing the size of the cells yields a trade-off between the accuracy and speed of the algorithm. Vicentini (2012) follows a similar approach in his dynamic model, dividing the city of Greensboro into cells of 2.25 square miles (1.5x1.5).

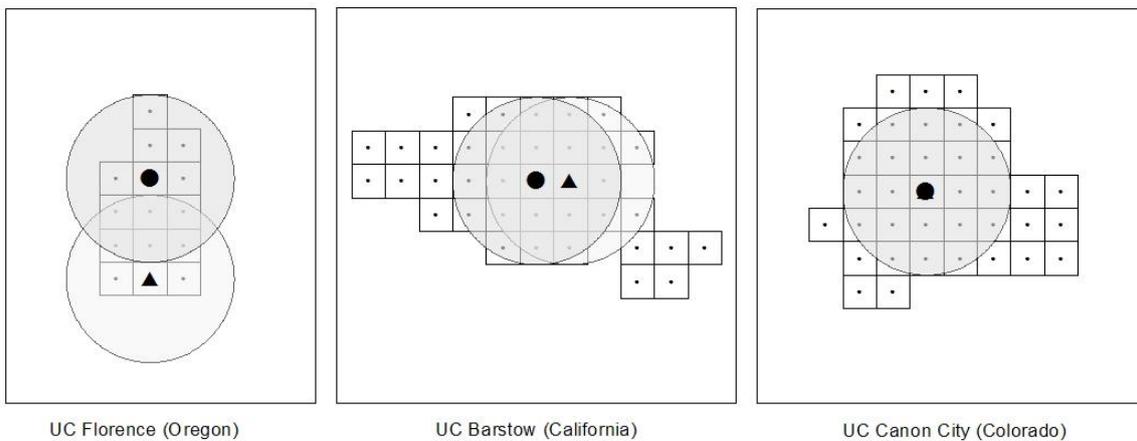
Figure 4: Data visualization for some sample markets.



(a) Discretized locations



(b) Population distribution



(c) Trade areas

tribution distances to the closest DC of the respective firms measured as the Euclidean distance in hundreds. $BB_distance$ is the distance to the closest big-box store of either Wal-Mart or Target, measured in hundreds of miles from the store location. av_Age and av_HHsize are the average age and the average household size of the population within the stores' trade areas.

Regarding the endogenous variables of the model, $Captive/\bar{X}$ indicates the fraction of captive consumers for the store and $\Delta Captive/\bar{X}$ defines the difference in captive consumers with respect to the rival, normalized by the population of the trade area of the firm.

The data indicate that for the firms considered, on average 13% and 14% respectively of the population in the trade area are captive. Note that we observe complete monopolization as well as markets with firms located at the same location. Considering the difference in the share of captive consumers with respect to a competitor, there is no statistical difference in the means of the two firms, implying that statistically there is no systematic dominance of one or the other player.

Since these statistics are the outcome of the location decision, but the decision-making is modeled as an incomplete information game, note that the domain of the expected number of captive consumers (corresponding to the range of f_2) is $(0, 1)$, which is due to the positive choice probabilities for each location alternative and Data Requirement 2.

Additionally, I also check the correlation between the number of captive consumers of the two firms providing Pearson's linear correlation coefficient $\rho_{captive}$. This is necessary for identification. If, for example, one firm always established itself in the city center while the other one was situated closer to the border, the profit specification (2) would suffer from multicollinearity. However, I find that there is no such significant correlation in the data.

Appendix C provides some summary statistics about the population distribution within markets. Note that for some locations, due to urban restrictions (e.g., parks), the population can be zero, but as can be seen from Table I, the population of a trade area is never zero and so the endogenous variables will always be defined.

Table I. Descriptive statistics of observed location choice.

Variables	observed outcomes					
	Kroger		Safeway			
	mean	st.dev.	min	max	min	max
exogenous variables:						
\bar{X}	15.0625	(10.7861)	0.8196	44.3463	15.2931	44.3463
Z	1.1495	(0.7075)	0.2841	3.2698	1.1615	2.8767
$BB_distance$	0.0644	(0.1188)	0.0012	0.4672	0.0597	0.4242
av_Age	39.4228	(6.7055)	25.0114	54.4940	39.4624	54.5760
$av_HH\ size$	2.3810	(0.2217)	1.9098	2.8331	2.3672	2.7899
endogenous variables:						
$Captive/\bar{X}$	0.1280	(0.2613)	0	1	0.1392	1
$\Delta Captive/\bar{X}$	-0.0756	(0.3196)	-1.5661	0.3780	0.0177	0.6103
$\rho_{captive}$	0.1791					
$(p - value)$	(0.3349)					

5 Estimation results

Estimating the model as outlined in Section 3, Table II reports the estimated parameters in the profit function of the firms for model specifications (1) and (2).

In order to evaluate the significance of the parameters and test their coherence with the theory, I use the bootstrap percentile method. I generate for each specification 300 re-samples with replacements from the original set of markets, solve the problem for each sample and calculate the percentile confidence intervals for the parameters. Appendix E provides the details of the bootstrap distributions.

Table II. Estimation Results.

Variables	without rivals		with Big Box rivals	
	model (1)	model (2)	model (3)	model (4)
\bar{X}	0.2794**	0.3473*	0.2909**	0.2649**
$\frac{Captive}{\bar{X}}$	1.5977*	1.3320**	1.0367*	1.3548**
$\frac{\Delta Captive}{\bar{X}}$	-0.2282**	0.3624**	-0.1824**	0.3469
$\frac{\Delta Captive}{\bar{X}} \times (1 - \frac{Captive}{\bar{X}})$		-0.9113**		-0.8702**
Z	-1.5302*	-1.6297*	-1.6594*	-2.0040**
BB_distance			1.1928	0.5026**
# Iterations	25	135	90	54
Log-likelihood	-149.6538	-142.6685	-147.6514	-138.9203

* Significance at the 10% level. ** Significance at the 5% level.

Models (3) and (4) provide a robustness check of the results with respect to other rivals. Further robustness checks, with respect to the specification of the distribution costs and some demographic characteristics of the potential consumers, turned out to be worse in terms of the log-likelihood and the convergence properties (see appendix, Table III).

The baseline model (other rivals disregarded):

Population distribution. The population within the trade area of the stores (measured in thousands) has a significant positive effect on the location choice of the firm, which captures the attractiveness of densely populated areas.

Market power and price-competition effect. The positive effect of a high fraction of captive consumers in model (1) as well as in model (2) captures the market-power effect. The bootstrap analysis for model (1) suggests that we can be at least 95% certain that the structural estimates are consistent with the outlined economic intuition, i.e., a positive effect of the percentage of captive consumers and a negative profit-effect of the difference with respect to the rival. Given a certain population in the firm's trade area, the higher the percentage of captive consumers, the larger the profit of the firm, which can be jus-

tified by the increased price-setting power of the firm. However, the negative effect of the difference in captive consumers with respect to the competitor, which captures the price difference of the firms, suggests that an advantage in terms of captive consumers with respect to the rival has a negative effect on the firm's profits. Exactly how this effect arises becomes more clear when we consider model specification (2), which allows for an interaction effect with the percentage of consumers living in the competitive area, namely those who care about price differences when choosing which store to buy from. While the effect of the difference in captive consumers becomes positive, the interaction effect indicates that this effect decreases along with the fraction of consumers in the competitive area. Considering the total effect of the difference in captive consumers, I find that if the fraction of consumers in the competitive region is above a threshold of 40 %, then an increase in the difference in captive consumers has a negative-profit effect. That is, contrary to my expectations, I find that an increase in the strategic variable which captures the price difference between firms does not always have a negative-profit effect but depends upon the market structure. I will discuss this later in more detail.

Distribution costs. Considering the cost effect, as expected, I find a significant negative-profit effect of the distribution distance, which is consistent with other retail studies (e.g., Vitorino (2012), Zhu and Singh (2009)) and which confirms the findings in Erdmann (2013).

Presence of other rivals:

Another important issue in the present competition analysis for the two main traditional supermarkets concerns other grocery retailers. We may think of other supermarkets and hypermarkets as well as alternatives like fresh stores and organic food stores. Last, but not least, the recently emerging small-format value-priced stores are also potential competitors for conventional supermarkets. In this paper, I assume that consumers regularly buy all their food products all at once at a single store, i.e., that consumers are assumed to buy a 'standard shopping basket', and I abstract from the possibility of buying some items from other grocery retailers.⁹ This assumption allows us to focus on those rivals who are not on a par with the firm in question but who are able to 'steal' a significant number of potential consumers from it. In order to identify these rivals, we rely upon the information provided by each firm. Safeway classifies its competitors in terms of primary conventional supermarkets and other rivals like big-box stores and warehouses or discounters (Safeway Fact Book 2011). Given the availability of the data, I focus exemplarily

⁹Allowing consumers to buy from multiple stores could be captured using the empirical approach of Huff (1964). However, it requires data on the frequency of purchase at each type of store, and it is a rather unusual approach in empirical industrial organization.

on the market presence of the big-box stores Wal-Mart and Target as rivals of a larger format which have repeatedly been demonstrated to have an effect on the conventional supermarket competition (e.g., Jia (2008), Matsa (2011)). Models (3) and (4) account for the distance between a supermarket location and the closest big-box retailer.

Considering model (3), the presence of these rivals is not significant. However, note that, compared to model (1), the market-power effect as well as the competition effect decrease somewhat in absolute terms, which may suggest that the isolated analysis without the consideration of other rivals slightly overestimates the strength of competition between the two firms. In contrast, the distribution-cost effect becomes slightly stronger in absolute terms. Model (4), in turn, which yields the largest log-likelihood, identifies a significant positive-profit effect of the distance to the closest superstore. This implies that the competitive pressure of this format diminishes with the distance to the store. Note also that, accounting for the presence of other rivals, the difference in captive consumers is no longer significant, while the interaction term with the fraction of consumers in the competitive area remains negatively significant. These results suggest that the threshold argument from model (2) no longer holds when I control for other rivals. In other words, taking into account the presence of other rivals, I find a clear negative-price competition effect that becomes stronger as the competitive area becomes relatively more important for the firm.

Finally, considering all the identified profit determinants, note that the 'hunt for captive consumer' can outweigh the attraction of densely populated locations; however, given a strong position of the rival in terms of captive consumers, locating close but in a less attractive area, the firm can gain a large fraction of the consumers in the competitive area, which may be an attractive strategy if the competitive area is sufficiently densely populated. Taking both arguments together, the model can explain observed spatial segmentation as well as observed spatial closeness, for example, with one firm in a high populated area and another one close by.

6 Discussion

6.1 On the role of captive consumers

I have proposed a model that uses the measure of 'captive consumers' to draw inferences from the various incentives that lead retailers to a certain location decision when anticipating price competition. The application to the supermarket data of Kroger and Safeway suggests that the behavior of the two firms is consistent with location-price competition as suggested by the toy model, in particular the interplay between the competition-based pricing strategies and the population distribution (the latter of which is anticipated by the firms when choosing their locations in the market).

To be precise, I find that the percentage of captive consumers in a retailer's trade area has a significant positive profit-effect. This implies that firms benefit from market power through spatial differentiation. Additionally, I find that the differences between captive consumers can have a negative profit-effect depending upon the market structure (i.e., with an increasing percentage of captive consumers, the consumers in the competitive area become less important for the firm up to a point of ignorance, and hence the price-competition effect becomes less important in the profit maximization of the firm).

However, the presence of other rivals provides an outside option for consumers, and hence debilitates the firm's monopoly power so much that alternatively acting as a monopolist in the captive region is not an option for the firm, which is reflected in the clearly negative effect of the difference between captive consumers, which increases with the size of the overlapping market area.

While the identified 'market-power effect' could also be justified under Cournot competition, the 'difference between captive consumers', which lets us infer the firm which sets a higher price and hence draws fewer consumers from the overlapping market area, is characteristic of Bertrand competition.

6.2 Comparison to other studies

Comparing the results to other game-theoretic location studies, note that the notion of 'returns to spatial differentiation' is similar to the concept of 'percentage of captive consumers'. Hunting for captive consumers goes necessarily along with spatial differentiation, but it additionally accounts for the population distribution over space.

In order to contemplate the difference between the present approach and studies using uniform radial competition effects, let us consider the model of Datta and Sudhir (2013) which models the endogenous location choices along with the choices of the types of stores. Although in my model the type (firm) is given exogenously and is restricted to markets with one store per firm, I use this example to illustrate the missing feature when firms compete in prices. Simplifying the model to a market with two firms only and adapting the notation to that used above allows a direct comparison of their profit specification,

$$\pi_{Fl}^e = \gamma_1 \bar{X}_l + \gamma_2 E[N_{-F,b=1}|Fl] + \gamma_3 E[N_{-F,b=2}|Fl] + \delta Z_{Fl} + \zeta + \omega_{Fl}$$

where $E[N_{-F,b=1}|Fl]$ is the conditional probability that the rival locates within a distance of up to D_2 miles, $E[N_{-F,b=2}|Fl]$ is the conditional probability that the rival locates within a distance of D_2 to D_3 miles from firm F , and ζ is a market-fixed effect. Note that this setting assumes that any rival location in a certain distance band of the store has the same competitive impact. If the neighborhood of a store location were to be characterized by local homogeneity in terms of the population distribution, this concentric ring approach

would be unproblematic. However, as illustrated in Figure 4, in many geographic markets this is not the case. That is, competitors located at different potential locations within a certain distance of the store count a different number of captive consumers as well as consumers in the overlapping market area with the store, and hence I expect them to exercise a different competitive pressure on the store. In other words, this specification ignores the effect of the population distribution on the price-setting power of the firm. If you nevertheless prefer the 'donut-approach' over the model proposed in this paper, as an alternative to account for location-specific competition effects, I suggest defining any measure of competitive pressure for each location in the respective donuts and weighting the expected number of stores within a donut by this competitive strength.

Note that the limitation of the radial approach comes from a direct transfer of consumer behavior to the firm behavior, which is not necessarily correct. Specifying a differentiated product-demand model (e.g., Davis (2006) and de Palma et al. (1994)), it is reasonable to assume that, whenever products are only differentiated in their geographic location, consumers' indifference curves are concentric circles around their locations. However, when the firms are choosing locations, which implies reaching some consumer locations and others not, their 'indifference curves', which are isoprofit curves, are not necessarily concentric rings. This comes from the fact that, for the firm, the population distribution matters in its choice, while when analyzing consumer behavior the individual decision is independent of the population distribution (unless in the case of network products).

The importance of accounting for the population distribution when empirically measuring strategic effects has also been emphasized for the estimation of structural-demand models in space. Using firm locations and price data, Davis (2006) estimates a retail-demand model under spatial differentiation using a BLP-approach. Beyond the typical BLP-instruments, employing the product characteristics of the rival, he exploits the spatial structure of the demand using population counts in the close locality of the rival as a valid instrument for prices. Note that, implicitly, this idea is in line with the concept of captive consumers.

Likewise, the literature on gravity models allows a comparison with our results. For an overview, see Anderson et al. (2009). These models go back to Reilly's Law of retail gravitation, and later, Converse's revision, in order to define a breaking point between retailers, which defines the 'indifferent consumer'. This approach defines the ability of a firm's location to attract consumers from a third (competitive) area as a decreasing function of the distance and an increasing function of the population at the store location. Note that the latter contradicts our argument. Their argument, which predicts greater 'competitive demand' for locations with a higher population, is based on the 'agglomeration' principle. However, given the difference in retail patterns in metropolitan areas, Mason and Mayer (1990) argue that Reilly's model works well in rural areas but not in UAs, and propose inverting the breaking-point formula such that the demand drawn from the competitive area increases as the population density decreases. Note that this is in

line with my findings, the difference being that I base my arguments on a game-theoretic framework.

6.3 Limitations and further research

My model has the following limitations. First, by the nature of the model and the computational methodology, I have identified a local maximum. Although I have run the model with many different starting points, I cannot guarantee that the equilibrium found is also global. Second, the study is limited to the competition between two firms operating one store each. My conjecture is that the main result is similar for markets with more than one store per firm, but this generalization would require some additional information on the firm's pricing practice across stores within a local geographic market. Firms can either follow a uniform pricing strategy, setting the same price for all stores within a geographic market, or practice price flexing, setting different prices across stores of the same chain. Depending upon the strategy played by the firms, Krčál (2012) shows that the outcome in terms of firm locations and shopping costs incurred by consumers can differ substantially. Unfortunately for the application to US supermarkets, there is no evidence about the local pricing strategy of a supermarket operating more than one store within a market. Furthermore, I have focused on a covered trade area, which allows for a straightforward comparison with the modified Hotelling version to interpret the results. Relaxing this model assumption, specifying consumer attraction as a decreasing function of the distance to the store, for instance, using a retail gravity model, is not expected to change the results, but it may provide additional insights.

7 Conclusion

I have provided an econometric location model under price competition that can be estimated with publicly available location data and the population distribution at the smallest possible unit. In the application to supermarkets, I find evidence of price competition, in particular that firms anticipate the degree of price competition in their location choice. I also find that firms consider distribution costs when choosing a location, and confirm that geographic differentiation from the competitor can increase profits.

As a policy implication, the local antitrust authorities may use the outlined mechanism to set up appropriate zoning restrictions in order to avoid excessive market power and promote a high degree of price competition.

Last, but not least, I hope that my analysis also motivates location analysis in business practice to take the outlined strategic location determinants into account.

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A Toy model

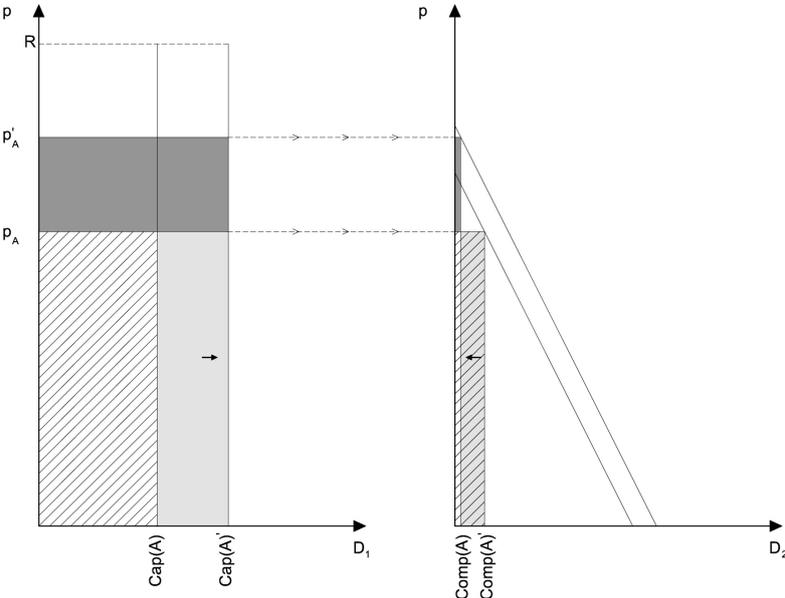
Here, I provide some exercises and the main insights derived from using the Hotelling framework as a simplified market setting as illustrated in Figure 1. This exercise is especially relevant for the theoretical understanding of the firms' strategy, and will be useful for the interpretation of the empirical results.

Normalizing the competitive area to one, i.e., $\bar{A}B - 2a \equiv 1$, so that $Comp = 1$, $\hat{X}_A = \frac{X_A}{Comp}$, $\hat{a} = \frac{a}{Comp}$, $\hat{X}_B = \frac{X_B}{Comp}$, the demand of firm A is defined as $\hat{D}_A = \hat{X}_A + \hat{a} + (\tilde{x} - \hat{a})$. The last term defines the demand drawn from the competitive region, which is specified by the indifferent consumer as usual. However, contrary to the standard Hotelling framework, we may have situations where only one firm draws demand from the competitive area. That is, $\tilde{x} - \hat{a} = \frac{1}{2} - \frac{p_a - p_b}{2t}$ if $|\frac{\Delta p}{2t}| \leq \frac{1}{2}$, $\tilde{x} - \hat{a} = 0$ if $\frac{p_a - p_b}{2t} > \frac{1}{2}$, and $\tilde{x} - \hat{a} = 1$ if $\frac{p_a - p_b}{2t} < -\frac{1}{2}$. Suppose for a moment that both firms draw demand from the competitive area. Then, solving the firm's optimization problem $Max \left\{ p_a \left(\hat{X}_A + \hat{a} + \frac{1}{2} - \frac{p_a - p_b}{2t} \right) \right\}$, maximizing over p_a the best response of the firm is $p_a = t(\hat{X}_A + \hat{a} + \frac{1}{2}) + \frac{1}{2}p_b$ and analog for firm B. Solving the simultaneous equation system, the optimal pricing strategy for firm A becomes $p_a^* = \frac{4}{3}t(\hat{X}_A + \hat{a}) + \frac{2}{3}t(\hat{X}_B + \hat{a}) + t$, and the analog $p_b^* = \frac{4}{3}t(\hat{X}_B + \hat{a}) + \frac{2}{3}t(\hat{X}_A + \hat{a}) + t$, such that the prices are a function of the travel-cost parameter t and the number of captive consumers. Hence, the demand that A draws from the competitive region becomes $\tilde{x} - \hat{a} = \frac{1}{2} + \frac{1}{3}\Delta\hat{X}_A$. This implies that both firms target the competitive area iff $|\Delta\hat{X}_A| \leq \frac{3}{2}$ and they generate profits from the captive area (π_{A1}) as well as from the competitive area (π_{A2}), i.e., $\pi_A = \pi_{A1} + \pi_{A2} = p_a^*(\hat{X}_A + \hat{a}) + p_a^*(\frac{1}{2} - \frac{1}{3}\Delta\hat{X}_A)$. However, if $\Delta\hat{X}_A < -\frac{3}{2}$, firm A will receive all the demand from the competitive area while B's optimal strategy generates revenues only from its captive consumers, setting the monopoly price. Considering only the revenues generated from the competitive area, I calculate the demand elasticity of competitive consumers as $\epsilon_{(\tilde{x}-a)} = -\frac{1}{3} \frac{\hat{X}_A + \hat{a}}{(\tilde{x} - \hat{a})}$. Whenever $\hat{X}_A + \hat{a} > \frac{1.5 + \hat{X}_B + \hat{a}}{2}$, the demand is elastic so that an increase in captive consumers reduces the revenues from the competitive area. Figure 5 illustrates this situation.

Alternatively, normalizing the trade area of the firm to one (i.e., $X_A + a + Comp \equiv \bar{X}_A = 1$) allows us to interpret the firm's strategic behavior as a function of the percentage of captive consumers in its trade area $(X_A + a)/\bar{X}_A$ and the normalized difference in captive consumers $\Delta X_A/\bar{X}_A$, respectively. Under this normalization, I ask whether there exists a critical number of captive consumers for which the firm is better off setting the monopoly price instead of engaging in price competition in the competitive area. This is equivalent to asking whether there is a solution to $\pi_A^M \geq \pi_{A1} + \pi_{A2}$. Hence, denoting R as the consumers' reservation price and solving the game, the inequality becomes $R(X_A + a) \geq p_a^* \left(\frac{X_A + a}{X_A} + \frac{\tilde{x}^*}{\bar{X}_A} \right)$ with $p_a^* = \frac{4}{3}t \frac{X_A + a}{X_A} + \frac{2}{3}t \frac{X_B + a}{X_A} + t \left(1 - \frac{X_A + a}{X_A} \right)$ and $\tilde{x}^* = \frac{(1 - \frac{X_A + a}{X_A})}{2} - \frac{1}{3} \left(\frac{X_A + a}{X_A} - \frac{X_B + a}{X_A} \right)$. For any given number of captive consumers of the rival $(X_B + a)$, there exists an upper bound

on the percentage of captive consumers $(X_A + a)/\bar{X}_A$, such that for a sufficiently high reservation price of the consumers (=monopoly price), the firm is better off focusing on the captive consumers to extract their surplus instead of competing over the competitive area. For instance, suppose that $X_B + a = 0$, then the inequality above can be written as a quadratic equation that has a solution if the discriminant $D = (\frac{1}{3} - R)^2 - 4 \cdot \frac{1}{18}t \cdot \frac{1}{2} \geq 0$. Setting $t = 1$, a solution exists if $R \geq \frac{2}{3}$. For example, setting $R = 1$ implies that a fraction of captive consumers higher than 80 % induces firm A to set the monopoly price, although for a fraction of captive consumers less than 120 %, both firms could draw positive demand from the competitive area.

Figure 5: The effect of an increase in captive consumers.



B Detailed calculations of variables

B.1 Two firms with one store each

The number of consumers within a maximal travel distance D_{max} who may patronize the store at l is calculated as follows:

$$\bar{X}_l = \sum_{l': d(l, l') \leq D_{max}} X_{l'}$$

where $X_{l'}$ is the population mass living at location l' and $d(l, l')$ is the Euclidean distance from location l to location l' . Note that this variable is the same for all stores and is independent of the rivals' choices.

Given asymmetric information about a rival's location determinants, firm F calculates expectations over the number of captive consumers for itself and for the rival firm in question based upon the beliefs (BP_k^{-F}) about the location choice of the rival,

$$E_{BP^{-F}}[Captive_{Fl}] = \sum_{l'} A(l, l') \cdot (1 - \phi_{l'}^{-F}) \cdot X_{l'} \quad (B.1)$$

$$E_{BP^{-F}}[\Delta Captive_{Fl}] = \sum_{l'} (A(l, l') - \phi_{l'}^{-F}) \cdot X_{l'} \quad (B.2)$$

where $\phi_{l'}^{-F}$ is the conditional probability that location l' is covered by the rival. The probability that a certain location l' is covered by the rival is the sum over the beliefs of F for the subset of locations that can be reached by a consumer who lives at l' , i.e., $\phi_{l'}^{-F} \equiv P(\text{covered}_{-Fl'} = 1 | \mathcal{I}_m^F) = \sum A_{kl'} \cdot BP_k^{-F}$, where A is a symmetric feasibility matrix of dimension $L \times L$ with elements $A_{kl'}$, taking the value '1' if a store at k can reach consumers at l' , and zero otherwise. Considering the firm's location choice l , if the store reaches location l' , then this location is 'covered by F' and the probability that the location is 'not covered' by the rival corresponds to the probability of the location in question being captive. Summing over the probabilities for all the locations that are within the trade area of F at l , and multiplied by the corresponding consumer mass $X_{l'}$, yields the total number of expected captive consumers as defined by equation (B.1).

The expected difference in captive consumers requires to calculate the captive consumers of the rival firm which, analogously to the calculation for the captive consumers of F , can be written as $E_{BP^{-F}}[Captive_{-Fl}] = \sum (1 - A(l, l')) \cdot \phi_{l'}^{-F} \cdot X_{l'}$. Hence, the expected difference between captive consumers is given by $Captive_{Fl}^e - Captive_{-Fl}^e$, which yields equation (B.2).

B.2 Generalization to multistore firms using uniform pricing

Since the model with one store for each firm is just a special case of the extension to markets with N stores, I provide here the calculation for the general case, with $s(F)$ denoting a store with a firm affiliation F and assuming that prices are set at the market-firm level (uniform pricing) while the location choice takes place at the store level.

For the ease of the calculation, let us first consider the variables under full information. The total number of captive consumers for chain F (i.e., who cannot reach any store of the rival chain) can be written as follows,

$$Captive_F = \sum_l captive_{Fl} \cdot X_l \equiv f(d_F, d_{-F}, A, X)$$

$$\text{with } captive_{Fl} = I \left\{ \underbrace{\sum_{s(F)} \sum_{k=1}^L d_{s(F)k} A_{kl} > 0}_{covered_{Fl}=1} \right\} \cdot \left(1 - I \left\{ \underbrace{\sum_{s(-F)} \sum_{k=1}^L d_{s(-F)k} A_{kl} > 0}_{covered_{-Fl}=0} \right\} \right)$$

where $captive_{Fl}$ is a dummy variable taking the value one if location l is captive for firm F , and zero otherwise. The rival's location is indicated as a vector d_{-F} of dimension $L_m \times 1$ with elements d_{-Fk} being dummy variables that take the value '1' if firm $-F$ chooses location k , and 0 otherwise. If any of its stores reaches location l , then I label this location 'covered by F '. If, additionally, the location is 'not covered' by the rival, then I label it a 'captive location'.

Under asymmetric information, the generalized probability of a location being covered can be written as follows:

Proposition 1. *If a store $s(-F)$ locates at l , the probability that location l' is covered by any F -store is given as follows, $\phi_{l'}^{F, N_F} \equiv Pr(covered_{Fl'} = 1) = 1 - (1 - \sum_k A_{kl'} \cdot BP_k^{s(F)})^{N_F}$, with BP^F being the beliefs about the location choice of a store with a chain affiliation F .*

Analog the one-store case, based on $\phi_{l'}^{F, N_F}$, it is straightforward to determine the number of consumers in competitive areas and captive regions, at the store level as well as at the firm level. The expected number of 'competitive consumers' at the store level is just the expected number of consumers within the feasible market range that are 'covered' by the rival:

$$E[Comp_s | s(F)l] = \sum_{l': d(l, l') \leq D_{max}} \phi_{l'}^{-F, N_{-F}} \cdot X_{l'}$$

However, what matters is the total number of consumers in the competitive areas, such that the expectations considering all stores are calculated as follows:

$$\begin{aligned} E[\text{Captive}_F | s(F)l] &= f_{s(F)l}^e(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) \\ &= \sum_{l'} \left[[\phi_{l'}^{F, N_F-1} (1 - A(l, l')) + A(l, l')] \cdot (1 - \phi_{l'}^{-F, N-F}) \right] \cdot X_{l'} \end{aligned}$$

$$\begin{aligned} E[\text{Captive}_{-F} | s(F)l] &= f_{s(-F)l}^e(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) \\ &= \sum_{l'} \left[[(1 - \phi_{l'}^{F, N_F-1}) (1 - A(l, l'))] \cdot \phi_{l'}^{-F, N-F} \right] \cdot X_{l'} \end{aligned}$$

$$\begin{aligned} E[\Delta \text{Captive}_F | s(F)l] &= g_{s(F)l}^e(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) = f(\cdot) - g(\cdot) \\ &= \sum_{l'} \left[[\phi_{l'}^{F, N_F-1} (1 - A(l, l')) + A(l, l')] - \phi_{l'}^{-F, N-F} \right] \cdot X_{l'} \end{aligned}$$

Note that for the particular case with two stores, with one of each chain ($N_F = N_{-F} = 1$), the structural variables are linear in terms of beliefs.

Proof of Preposition 1.

$$\begin{aligned}
E[\text{Captive}_F] &= E[f(d_F, d_{-F}, A, X)] \\
&= E\left[\sum_l \text{captive}_{Fl} \cdot X_l\right] = \sum_l E[\text{captive}_{Fl}] \cdot X_l \\
&= \sum_l E\left[I\left\{\sum_{k=1}^L d_{Fk} A_{kl} > 0\right\} \cdot \left(1 - I\left\{\sum_{s=1}^L d_{-Fs} A_{sl} > 0\right\}\right) | s(-F)\right] \cdot X_l \\
&= \sum_l P(\text{captive}_{Fl} = 1) \cdot X_l \\
&= \sum_l P(N\text{covered}_{Fl} \geq 1 \cap N\text{covered}_{-Fl} = 0) \cdot X_l
\end{aligned}$$

by Conditional Independence Assumption:

$$= \sum_l P(N\text{covered}_{Fl} \geq 1) \cdot [1 - P(N\text{covered}_{-Fl} \geq 1)] \cdot X_l$$

(1.) for $N_F = 1$:

$$\begin{aligned}
P(\text{covered}_{s(F)l} = 1) &= E\left[I\left\{\sum_{k=1}^L d_{s(F)k} A_{kl} > 0\right\}\right] \\
&= P(d_{s(F)1} A_{1l} = 1 \cup d_{s(F)2} A_{2l} = 1 \cup \dots \cup d_{s(F)l} A_{ll} = 1)
\end{aligned}$$

by Mutually Exclusive Choices:

$$\begin{aligned}
&= \sum_k P(d_{s(F)k} A_{kl} = 1) \\
&= \sum_k A_{kl} \cdot P(d_{s(F)k} = 1) \\
&= \sum_k A_{kl} \cdot EP_k^{s(F)} \equiv \phi_l^s(BP^{s(F)}) \quad \text{result how firms form their expectations}
\end{aligned}$$

(2.) for $N_F \geq 1$:

$$\begin{aligned}
P(N\text{covered}_{Fl} \geq 1) &= E\left[I\left\{\sum_{s(F)} \sum_{k=1}^L d_{s(F)k} A_{kl} > 0\right\}\right] \\
&= E\left[1 - I\left\{\sum_{s(F)} \sum_{k=1}^L d_{s(F)k} A_{kl} = 0\right\}\right] \\
&\text{since } \text{covered}_{s(F)l} \sim \text{Bernoulli}(\phi_l^s) \\
&\Rightarrow N\text{covered}_{Fl} \sim \text{Binomial}(N_F, \phi_l^s) \\
&= 1 - P(N\text{covered}_{Fl} = 0) \\
&= 1 - (1 - \phi_l^s)^{N_F} = 1 - \left(1 - \sum_k A_{kl} \cdot BP_k^{s(F)}\right)^{N_F} \equiv \phi_l^{F, N_F}(BP^{s(F)})
\end{aligned}$$

C Markets

Table C1. Discrete population distribution within the sample markets

UA/UC (ID)	Name (State)	L	Av. pop/loc*	Std.dev.	Min	Max
847	Alamosa (CO)	12	0.3997	(0.2297)	0.0235	0.7275
955	Albany (OR)	41	1.2223	(1.5334)	0.0451	7.3970
3547	Astoria (OR)	28	0.2072	(0.2512)	0.0000	0.9583
5302	Barstow (CA)	37	0.6823	(1.1847)	0.0062	5.2514
11431	Bullhead City (AZ)	55	0.8104	(1.1928)	0.0245	6.5929
13267	Canon City (CO)	37	0.7244	(1.1034)	0.0038	5.000
14158	Carson City (NV)	60	0.9702	(1.7270)	0.0179	9.7462
14401	Casa Grande (AZ)	41	1.1651	(1.5624)	0.0211	6.7474
17020	The Dalles (OR)	30	0.7394	(1.4726)	0.0060	6.2118
20368	Cortez (CO)	19	0.3867	(0.5963)	0.0301	2.500
20557	Cottonwood (AZ)	35	0.6224	(0.8030)	0.0049	2.5872
20827	Craig (CO)	15	0.7369	(1.2891)	0.0112	4.7438
23230	Delta (CO)	15	0.4674	(0.6490)	0.0054	1.9948
26983	Ellensburg (WA)	16	1.3426	(2.3313)	0.0042	7.9152
30034	Florence (OR)	15	0.8056	(0.8199)	0.0162	2.1213
32491	Galveston (TX)	32	1.4669	(2.9546)	0.000	10.660
33652	Glenwood Springs (CO)	30	0.1801	(0.3235)	0.0020	1.2994
36001	Ginnison (CO)	16	0.2738	(0.4421)	0.0013	1.2394
46747	Lake Havasu City (AZ)	51	0.8841	(0.9946)	0.0012	2.9632
59437	Morro Bay (CA)	35	0.7277	(1.2567)	0.0000	4.9571
62839	Newport (OR)	18	0.4912	(0.8911)	0.0000	3.1125
63514	North Bend (WA)	31	0.5433	(0.7387)	0.0066	3.7391
75367	Riverton (WY)	18	0.7144	(0.8853)	0.0050	3.0414
76339	Roseburg (OR)	53	0.7172	(1.0468)	0.0181	4.2613
77527	St. Helens (OR)	43	0.4857	(0.6949)	0.0307	3.4343
80686	Sequim (WA)	24	0.6345	(0.6736)	0.0000	2.7324
81415	Shelton (WA)	36	0.3390	(0.5840)	0.0000	2.7229
81901	Sierra Vista (AZ)	121	0.4313	(1.0137)	0.0000	5.2250
84682	Steamboat Springs (CO)	25	0.2402	(0.3711)	0.0209	1.5894
89920	Vail (CO)	11	0.0827	(0.0513)	0.0451	0.1624
97966	Yucca Valley (CA)	45	0.4428	(0.4960)	0.0047	1.7297

* population density in 1000

Table C2. Market selection

	both chains with one store each (estimation sample)	both chains active & $L \leq 500$	both chains active(3)
size (in mi ²)	14.11 (13.89)	43.50 (53.37)	153.12 (346.50)
population density (pop/mi ²)	1654.77 (673.72)	2029.84 (846.10)	2354.61 (1124.96)
households	8430.35 (5936.29)	40333.69 (70777.15)	198349.41 (542684.26)
locations (1×1 mile cells)	33.71 (20.79)	79.07 (72.90)	222.35 (438.48)
number of Kroger-stores	1 (0)	2.27 (4.76)	8.97 (25.50)
number of Safeway-stores	1 (0)	2.66 (2.99)	9 (19.23)
number of markets	31	71	103

* Standard errors in brackets.

The selection of isolated markets is a known potential selection problem in all the applied market entry papers based on Bresnahan and Reiss (1990,1991). For the application in this paper, I have chosen duopoly markets with one store each since I don't have information on the pricing policy of the firms in a multistore-markets which has a crucial impact on the optimal location decision of a firm Krčál (2012). Moreover, the chosen selection criteria allows me to study the strategic location choice under price competition in a simple framework, avoiding too much noise that is expected to increase with the market size (e.g. many other grocery retail formats for which we cannot control, unobservable spatial clustering, high heterogeneity across consumers, etc.).

D Knitro problem specification and outcome

As specified in Section 3, I formalize the equilibrium conditions of the game as nonlinear equality constraints. I leave the structural parameters unrestricted and define the choice probabilities as bounded on the interval $[0.00001, 1]$. The lower bound assumes that the selection probabilities are positive for all alternatives, which implies little loss of generality since, empirically, a probability of zero cannot be distinguished from such a small probability (McFadden, 1974). The upper bound is a hypothetical constraint that is active only if there is only one possible location in the market which is ruled out by Identification Requirement 2. Note that this setting provides a closed and bounded set for the choice probabilities. As initial values for the beliefs, I use a uniform distribution over all the locations within a market. For the structural parameters I use many different initial values, with the guess for the population coefficient and distribution distance based on the results from Datta and Sudhir (2013). For the implementation, I use numerical derivatives (first-difference approximation). I am aware of the efficiency improvement providing analytical derivatives, but given the complexity of the constraints which makes the hand-coded Jacobian error-prone, I was unable to code it correctly for the entire model, and hence I use numerical derivatives at the cost of higher CPU-time to avoid unnecessary bugs.

The output below provides the Knitro results for the baseline model specification (1), including the individual iteration steps and the final statistics.

Iter	fCount	Objective	FeasError	OptError	Step	CGits
0	1561	1.581178e+02	9.804e-01			
1	3122	2.435902e+02	1.000e+00	9.990e+04	4.132e+00	1
2	4683	1.294698e+02	9.688e-01	3.232e+04	1.854e-01	1
3	6244	2.250137e+02	5.707e-01	9.993e+04	2.352e+00	1
4	7806	2.046373e+02	7.097e-01	1.292e+05	1.388e+00	2
5	9370	1.936422e+02	4.259e-01	1.000e+05	1.286e+00	2
6	10933	1.869210e+02	7.464e-01	2.446e+05	4.556e-01	2
7	12494	1.879848e+02	6.260e-01	2.663e+05	6.258e-01	1
8	14058	1.819859e+02	5.109e-01	1.021e+06	6.059e-01	2
9	15623	1.783575e+02	4.165e-01	1.012e+06	2.216e-01	3
10	17184	1.752116e+02	2.336e-01	4.491e+05	2.812e-01	1
11	18745	1.734636e+02	3.273e-01	9.983e+04	5.624e-01	2
12	20308	1.677522e+02	6.379e-02	9.948e+04	2.812e-01	3
13	21869	1.611384e+02	2.446e-02	1.156e+05	2.812e-01	1
14	23431	1.535351e+02	1.258e-02	1.788e+05	2.912e-01	1
15	24995	1.502473e+02	3.122e-03	9.914e+04	2.686e-01	3
16	26556	1.502074e+02	1.775e-04	1.968e+02	1.401e-02	2
17	28123	1.501067e+02	2.878e-05	9.076e+03	9.434e-03	6
18	29685	1.499078e+02	1.711e-06	1.015e+04	1.887e-02	1
19	31249	1.497882e+02	8.663e-07	5.933e+03	1.223e-02	2
20	32813	1.497031e+02	4.105e-07	6.324e+03	7.912e-03	2
21	34377	1.496530e+02	2.835e-08	3.169e+03	4.760e-03	2
22	35942	1.496543e+02	1.758e-08	2.522e+03	1.371e-04	5
23	37504	1.496555e+02	6.814e-09	2.520e+03	1.371e-04	2
24	39066	1.496538e+02	1.472e-08	3.591e+00	1.371e-04	1
25	40633	1.496538e+02	1.443e-08	3.927e-01	3.748e-06	7

EXIT: Locally optimal solution found.

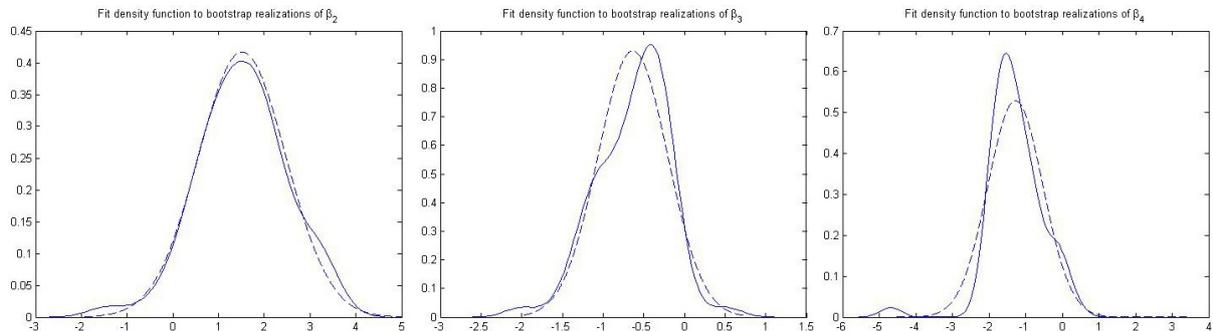
Final Statistics

Final objective value	=	1.49653815868534e+02
Final feasibility error (abs / rel)	=	1.44e-08 / 1.44e-08
Final optimality error (abs / rel)	=	3.93e-01 / 9.63e-05
# of iterations	=	25
# of CG iterations	=	56
# of function evaluations	=	40633
# of gradient evaluations	=	0
Total program time (secs)	=	1554.24536 (1554.585 CPU time)
Time spent in evaluations (secs)	=	866.77026

Notation: iteration number (Iter), cumulative number of function evaluations (fCount), value of the negative log-likelihood function (Objective), feasibility violation and the violation of the Karush-Kuhn-Tucker first-order condition of the respective iterations (FeasError, OptError), distance between a new iteration and the previous iteration (Step), number of projected conjugate gradient iterations required to compute the step (CGits).

E Bootstrap distribution

To determine the significance of the estimates, I use the bootstrap percentile method. Since the justification of this method rests on an approximately normal distribution of the parameters, let us as an exemplar have a detailed look at the bootstrap distribution of the parameters of model specification (1), providing the non-parametric density functions for the structural parameters. Note that the distribution could be approximated by a normal distribution.



Hence, based on those bootstrap estimates that reported convergence (approx. 80%), I calculate for each model specification and each parameter a 90% and a 95% confidence interval. Tables E1-E4 indicate the quantiles of interest and the probability of a negative coefficient.

Table E1. Bootstrap distribution model (1).

	$\beta_1^{(1)}$	$\beta_2^{(1)}$	$\beta_3^{(1)}$	$\delta^{(1)}$
2.5% percentile	0.1280	-0.4312	-1.5947	-9.7423
5% percentile	0.1549	0.2677	-1.4286	-4.6864
95% percentile	1.0299	3.2601	-0.1650	-0.0258
97.5% percentile	1.2311	3.2779	-0.0758	0.0145
prob. $\beta \leq 0$	0.00	0.04	0.99	0.96

Table E2. Bootstrap distribution model (2).

	$\beta_1^{(2)}$	$\beta_2^{(2)}$	$\beta_3^{(2)}$	$\beta_4^{(2)}$	$\delta^{(2)}$
2.5% percentile	-0.2392	0.7939	0.0883	-2.2971	-2.1172
5% percentile	0.1245	0.8266	0.1141	-2.2231	-2.1141
95% percentile	0.7417	2.9457	2.1987	-0.5243	-0.1710
97.5% percentile	0.8301	3.0037	2.3412	-0.4211	0.0599
prob. $\beta \leq 0$	0.03	0.00	0.00	1.00	0.95

Table E3. Bootstrap distribution model (3).

	$\beta_1^{(3)}$	$\beta_2^{(3)}$	$\beta_3^{(3)}$	$\delta^{(3)}$	$\gamma^{(3)}$
2.5% percentile	0.0791	-0.662	-1.4754	-2.5058	-0.4613
5% percentile	0.1921	0.0625	-1.3074	-2.1274	-0.3814
95% percentile	0.9927	3.0351	-0.1576	-0.2073	1.9518
97.5% percentile	1.0465	3.2201	-0.1225	0.3161	1.9956
prob. $\beta \leq 0$	0.00	0.04	0.99	0.95	0.18

Table E4. Bootstrap distribution model (4).

	$\beta_1^{(4)}$	$\beta_2^{(4)}$	$\beta_3^{(4)}$	$\beta_4^{(4)}$	$\delta^{(4)}$	$\gamma^{(4)}$
2.5% percentile	0.3313	0.9437	-0.0824	-1.0440	-1.5000	0.5681
5% percentile	0.2943	1.5397	-0.0495	-0.6354	-0.9063	1.1688
95% percentile	0.2426	0.5568	1.8205	-1.8995	-1.7471	0.2442
97.5% percentile	0.3616	2.2118	1.9206	-1.7789	-1.8498	0.2548
prob. $\beta \leq 0$	0.00	0.00	0.07	1.00	1.00	0.00

F Further robustness checks

Model (5) allows for a linear-quadratic shape of the distribution costs, and model (6) controls for average consumer characteristics, such as household size and age, within the trade area of the firm. Given the large number of iterations necessary to achieve convergence, I abstain from the computationally-intensive bootstrap analysis and report only the equilibrium results, which have to be interpreted with caution.

Table F. Further robustness checks.

Variables	(1)	(5)	(6)
\bar{X}	0.2794	0.2833	0.2556
$\frac{Captive}{\bar{X}}$	1.5977	1.5282	1.6168
$\frac{\Delta Captive}{\bar{X}}$	-0.2282	-0.3842	-0.5297
$\frac{\Delta Captive}{\bar{X}} \cdot (1 - \frac{\Delta Captive}{\bar{X}})$			
Z	-1.5302	-1.5635	-0.8151
Z^2		0.3888	
BB_distance			
Av_Age			0.2039
Av_HHsize			0.6612
# Iterations	25	328	2465
Log-likelihood	-149.6538	-158.4787	-181.2045

Allowing for a more flexible form of the cost structure, including the squared distance, suggests a U-shaped pattern which confirms the results from my previous work. Note that the market-power effect is robust to this functional variation of the cost structure, while the price-competition effect becomes slightly stronger. This sensibility regarding the costs structure may be carefully interpreted as the distribution costs also partially effecting the marginal costs, and hence the price setting.

The positive coefficients of age and household size suggest that traditional supermarkets are more likely to target 'older' people, which is to be understood in relative terms in the sense of families.

Further possible control variables might be the geographic income distribution and the social class of households. However, given the data limitations at the disaggregated level of block groups, I do not control for these and I assume implicitly that the reservation price of all households for a standard food basket at a supermarket store is high enough.