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TESIS DOCTORAL

Essays on Strategic Location Choices and Pricing Strategies in Oligopolistic Markets

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Getafe, junio de 2015

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Getafe, de de

Dedicated to the memory of my mother, Eleonore.

Declaration

I, Anett Erdmann, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Anett Erdmann

Madrid, June 2015

Abstract

The three chapters of this dissertation contribute to the understanding of strategic firm behavior in oligopolistic markets. In particular, I link spatial market features to standard competition analysis, which enables new perspectives to explain market outcomes in geographically defined markets and provide applications to the grocery retail industry.

Chapter 1 studies the importance of returns to product differentiation and distribution economies for a firm's optimal location choice. Inspired by the empirical work of Holmes (2011), I introduce endogenous distribution costs in the model of Hotelling (1929). The proposed model shows an interesting trade-off between demand and cost considerations when a firm plays a hybrid location strategy. Given the location of local distribution centers and agents' displacement cost parameters, it is shown that, under certain conditions, the optimal locations of the firms are in the interior of the Hotelling line rather than at the edges of the line. The supply-cost effect which drives this result diminishes with the distance of the distribution center from the market so that the scale of the distribution area also becomes determinant for an optimal location strategy.

Chapter 2 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 grocery stores operated by the two main conventional supermarket chains in the US, the model confirms the existence of benefits of spatial differentiation for the firms' profits and provides evidence that the firms anticipate price competition and distribution costs in their site selections.

Chapter 3 studies empirically the volatility of retail price indexes at the store level

as a result of changes in the local market structure within an urban market. Using a reduced-form pricing equation, I decompose the potential competition effect in the effect of incumbent retailers and the effect of new grocery store openings. Considering the Spanish supermarket industry, which is strongly regulated, I make use of panel data and use a first-difference approach to estimate a distributed-lag model. The results suggest an instantaneous price reaction to entry which is smaller than the long-term competition effect. Possible explanations are constrained price-flexibility for incumbent firms in the short run or difficulties of the entrant in establishing themselves as coequal rivals. I find that this gradual price reaction is especially pronounced for supermarkets positioned in the middle price-segment, and the strongest price reaction has been found for high-price retailers.

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CHAPTER 1

Hotelling meets Holmes

1.1 Introduction

For distribution-intensive industries with a strong cost focus and a high turnover rate of merchandize, business concepts suggest that the optimization of logistic costs plays a crucial role in being competitive (Andersen and Poulfelt, 2006). However, most of the economic models either do not account at all for distribution costs or else include them (implicitly) as exogenous fixed costs. Such a setting is in general unproblematic for market entry models but may be problematic in the context of optimal geographic differentiation between competing firms. A certain location decision considering demand and competition effects may be optimal for given fixed costs, but once we consider supply costs as part of the fixed costs, depending on the actual location of the firm and its distribution center, it might be profitable to locate closer to the distribution facility to decrease supply costs (although this may imply less differentiation to competitors). Inspired by the empirical work of Holmes (2011) which suggests the economic importance of distribution costs in the optimal location decision of a firm (Wal-Mart), this paper introduces endogenous distribution costs in the duopoly model of Hotelling (1929).

Such an environment causes a tension between the demand and supply strategy of location choice, which to the best of my knowledge has not been analyzed in a theoretical model of product differentiation and has not been subjected to an empirical analysis for oligopoly industries.

Considering the theoretical literature, the work-horse of spatial location choice is Hotelling's linear city model (1929) and the subsequent work by d'Aspremont et al. (1979). This model of price competition allows us to analyze product differentiation in a simple framework and has given rise to numerous extensions. For a review, see Anderson et al. (1992) or Tirole (1998). Recent examples are Meagher et al. (2008), analyzing the equilibrium existence under different consumer distributions, and Hamoudi and Moral (2005), considering linear-quadratic transportation costs for consumers. However, while the demand side has been extensively analyzed, the costs of the firms - in particular, product-specific fixed costs - have not received much attention. The theoretical literature is complemented by empirical and computational papers. For given supermarket locations, Matsa (2011) shows that the distance to a distribution center has a negative effect on the store's product availability. Considering endogenous location choice, the seminal work by Mazzeo (2002) and Seim (2006) provides empirical evidence for the market-power effect of product differentiation within a market, but cost strategies that may alter the optimal location decision remain unconsidered. The first empirical analysis incorporating supply aspects in an endogenous location choice model is Holmes (2011). He uses a computational analysis to show in a dynamic market entry model that the optimal location strategy of Wal-Mart is based on a trade-off between the proximity of stores to distribution centers and each store's demand cannibalization. His work has inspired other researchers to incorporate supply distances in empirical models of entry or location choice (e.g., Ellickson, 2010; Zhu and Singh, 2009; Vitorino, 2012).

This paper proposes a price-location game in which firms use hybrid location strategies considering cost-efficiency and horizontal competition simultaneously. On the demand side, consumers incur travel costs to buy at a certain store. On the supply side, each firm's store is stocked up daily by an (owned) exogenous distribution center, which can be located in or outside the linear market, and firms have to bear the supply costs. Consumers face quadratic travel costs while firms' displacement costs are modeled as a linear-quadratic function of the supply distance to allow for a more flexible shape since, in contrast to consumers, suppliers are allowed to 'travel' to firms from outside the market. Solving for the optimal location choice shows an interesting trade-off between returns to product differentiation and distribution economies. It is shown that, under certain conditions, and depending on the location of the distribution centers and the agents' displacement cost parameters, the optimal location of the firms are in the interior of the Hotelling line rather than at the edges of the market (maximal differentiation). The supply-cost effect, which drives this result through the

compensation of lower revenues with lower distribution costs, diminishes with the distance of the distribution center from the market so that the scale of the distribution area becomes crucial for an optimal location strategy. Finally, in the presence of distribution costs, firms are better off in terms of net profits when applying a hybrid location strategy rather than a pure demand-based location strategy. Considering the welfare implications of the dual location choice, it is shown that the incentive to generate market power through differentiation still leads to excessive differentiation, but less so than in the standard model if the supply cost parameter is sufficiently high relative to the consumers' transportation cost parameter.
The theoretical results are complemented with an empirical example for distribution-intensive grocery retailers using location data on the stores and distribution centers of the two main conventional supermarket chains in the US, namely Kroger and Safeway. I find that the two chains target similar markets and include distribution cost considerations in their location choice with respect to their competitors. In particular, I find a U-shaped pattern between the distribution distance and the differentiation to the competitor that is in line with the proposed theoretical model.

The next section presents the model and Section 1.3 provides the empirical application. In this paper, I refer to differentiation as a geographic element, but the presented mechanism can be generalized to further applications which are briefly outlined in Section 1.4.

1.2 The linear city with distribution costs

1.2.1 The model

The model setting is based on Hotelling's linear city model (1929) with quadratic transportation costs (d'Aspremont et al., 1979), which yields a well-defined equilibrium of maximal product differentiation. In this common setup, I introduce endogenous distribution costs which are carried by the firms as part of their fixed costs.

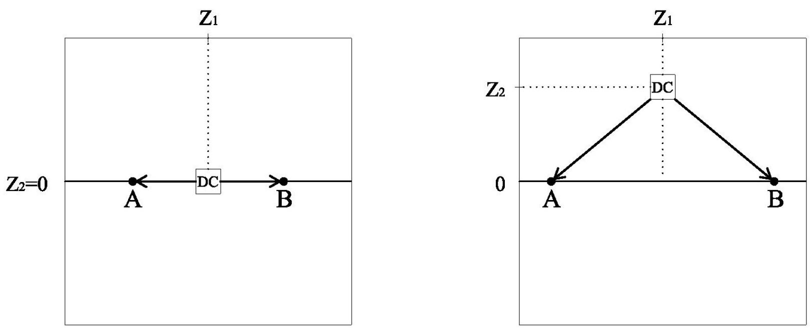
There are two firms, firm A and firm B, selling both homogeneous grocery baskets and competing in locations and prices. Fresh merchandize is delivered every day from a (firm's own) regional distribution center (DC). A continuum of consumers is uniformly distributed over a linear market of length r, $X \sim U[0, r]$ and each consumer buys just one grocery basket.[1] In addition to the standard model, both types of agents, consumers and firms face displacement costs, which significantly changes the equilibrium location strategy. On the demand side, consumers incur travel costs to buy at a certain store. On the supply side, each firm's store is stocked up daily by an exogenous DC, which can be located in or outside the linear market, and firms have to bear the supply costs.[2] The location of the DC in space is characterized as (z_1^a, z_2^a) and (z_1^b, z_2^b) respectively. We use a reference coordinate system where the linear market builds the horizontal axis and the left end of the market is defined as the origin of the coordinate system.[3] Hence, the shortest distance from the DC to the market can be directly indicated as $|z_2^j|$ and the orthogonal projection of a DC onto the market is just $(z_1^j, 0)$, with $j = \{a, b\}$. Figure 1.1 illustrates exemplarily two possible situations where both firms are supplied by a common DC. While in Figure (a) the firms are supplied by a DC which is situated in the linear market ($z_2 = 0$), Figure (b) illustrates a situation where firms are stocked up by a DC located outside the market. In the following, I refer to these two cases as *Market-DC* and *Non-Market-DC* respectively. Considering the consumer side, a consumer i who lives at x_i faces quadratic travel costs $TC_i(a) = t \cdot (a - x_i)^2$ if he buys from A and $TC_i(b) = t \cdot (r - b - x_i)^2$ if he buys from B, where t is the travel cost parameter and a and $r - b$ the respective firms' locations. The firms' displacement costs are specified in a similar way. Distribution costs are modeled as linear-quadratic functions of the supply distance, which can be reduced to a quadratic function for the simple case where the DC is located inside the market. We choose this cost specification to allow for a more flexible shape since, in contrast to consumers, suppliers are allowed to 'travel' to firms from outside the market. The distribution distance can be simply expressed as the hypotenuse of a right-angled tri-

[1] All consumers are assumed to buy so that the market is fully served.

[2] The exogeneity assumption of the DCs is easy to justify whenever the DCs belong to a third party or a firm leases already existing DCs of another chain (Recent example: Target entering the Canadian market). If the DCs are a firm's own, the DC location may be considered as an endogenous decision of the firm. In this paper, we abstract from this special case, focusing on firms that use *ex ante* established facilities or third party service providers.

[3] A similar framework of firms choosing their locations on a line while the environment is allowed to be two-dimensional is used by Thomadsen(2006). He places two heterogeneous fast-food stores on a line and lets them choose their optimal locations in terms of the distance from the center while consumers are distributed over a two-dimensional space.

FIGURE 1.1
THE LINEAR CITY WITH DISTRIBUTION COSTS.



(a) Market-DC (b) Non-Market-DC

angle between the DC and the store location. Hence, given the location of firm A's DC or exogenous supplier, the distribution costs for store A are given by

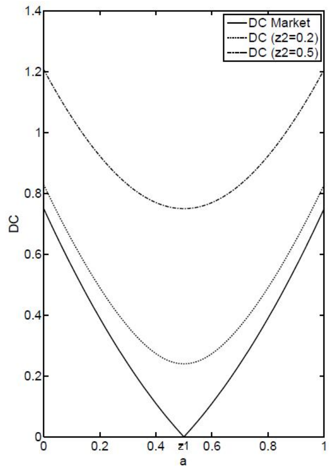
$$\begin{aligned} DC_a(a; z^a) &= d_1 \cdot (\textit{Supply Distance})^2 + d_2 \cdot (\textit{Supply Distance}) \\ &= d_1 \cdot \left[(a - z_1^a)^2 + (z_2^a)^2\right] + d_2 \cdot \sqrt{(z_1^a - a)^2 + (z_2^a)^2} \end{aligned}$$

where d_1 and d_2 are distribution cost parameters capturing the linear-quadratic shape of the supply cost function. To reduce the analysis to a non-negative, increasing and convex supply cost function, I assume $d_1 \geq 0$, $d_2 \geq 0$.[4] The specification includes the case of quadratic costs ($d_2 = 0$), which is illustrated in Figure 1.2. It is immediately clear that the distribution costs increase with the distance of the DC from the market. However, notice that the distribution cost effect of moving one unit closer to the projected distribution facility (z_1) increases the closer that the supplier is to the market (smaller z_2).

With this in mind, the firms' strategic decisions take place in two stages. First, firms A and B simultaneously decide upon their store locations, a and $r - b$, respectively.

[4]The linear-quadratic cost specification in Hotelling's model is not new. Hamoudi and Moral (2005), for example, use a linear-quadratic cost specification for consumers' travel costs to allow for concave transportation costs. We use a similar specification for the supply costs but impose the restriction of a convex cost structure. Instead of assuming $d_1 \geq 0$, the assumption could be relaxed, allowing for a non-monotonic shape of the cost function. In this case, and in order to guarantee a non-negative cost function, one might extend the cost specification to a general second-degree polynomial $DC_a(a; z^a) = d_0 + d_2 \cdot \textit{SDistance} + d_1 \cdot (\textit{SDistance})^2$ with at most one root. The additional term $d_0 \geq 0$ could be interpreted as fixed operation costs.

FIGURE 1.2
DISTRIBUTION COSTS.



$d_1 > 0,\ d_2 = 0$

The feasibility constraint of the location choice, which is indicated in terms of the distance from the market edges, implies that $a, b \in [0, r]$. Additionally, I assume that $a \leq b$. Once the two grocery firms are established, they compete in prices. The firms set prices p_a and p_b depending upon the degree of differentiation. Based on each firm's location and the prices offered, the utility-maximizing consumers face a discrete choice problem at which store to buy.

1.2.2 Equilibrium locations

Given the environment presented in the previous section, the game is solved recursively. Compared with the standard linear city model, the pricing stage does not change, and hence I will refrain from a detailed discussion of this stage.[5] The indifferent consumer is given by $\tilde{x} = \frac{p_b - p_a}{2t(r-b-a)} + \frac{r-b+a}{2}$ and the store demand is $D_a = \tilde{x}$ and $D_b = r - \tilde{x}$, respectively, so that the resulting optimal prices given any two store locations $(a, r-b)$ are $p_a^*(a,b) = c + t \cdot (r-a-b)r + 1/3 \cdot t \cdot (r-a-b)(a-b)$ and $p_b^*(a,b) = c + t \cdot (r-a-b)r - 1/3 \cdot t \cdot (r-a-b)(a-b)$.

Given the optimal pricing decision and the exogenous locations of the DCs, firm A chooses its optimal location solving the following problem:

[5]This is due to the setting analog Holmes (2011), defining the distribution costs as fixed costs independent of the sales volume. (By extension, we may additionally allow the unit variable costs to be an increasing function of the distribution distance so that the DC location determines directly the optimal pricing decision.)

$$\left\{ \begin{array}{c} Max_a[p_a^*(a,b) - c]D_a\left(p_a^*(a,b)\right) - DC_a\left(a; z_1^a, z_2^a\right) \\ s.t. \qquad a \in [0, r] \end{array} \right\}$$

Note that the firm's location choice enters not only in the demand but also in the cost function. Solving for a, under the first-order condition of the pricing stage, yields the following optimality condition for the firm's location choice:

$$FOC_a: \quad \underbrace{(p_a - c)\left[\frac{\partial D_a}{\partial a} + \frac{\partial D_a}{\partial p_b}\frac{\partial p_b}{\partial a}\right]}_{MRPD} \leq \underbrace{\frac{\partial DC_a}{\partial a}}_{MRDE} \tag{1.1}$$

The inequality condition (1) clearly indicates the trade-off between marginal returns on product differentiation (MRPDs), which reflects the competition effect, and marginal returns in the form of distribution economies (MRDEs). It captures the dual nature of location choice and its effect on a firm's profits. In other words, assuming $a < z_1^a$, if firm A moves marginally away from the extreme towards firm B, competition increases and revenues decrease, but at the same time the firm moves closer to the DC such that the firm saves on logistic costs.[6] If the savings on supply costs are bigger than the loss of revenues, it is optimal for the firm to move towards the competing firm at the cost of stronger price competition.

FIGURE 1.3
BEST LOCATION RESPONSE.

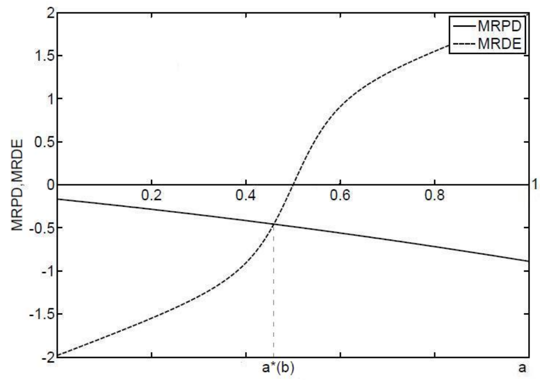


Figure 1.3 illustrates this trade-off. The profit is maximized where the MRPD equals the MRDE. The optimal location choice depends, on the one hand, on firm B's location choice and the consumers' travel cost parameter, which shifts the MRPD, and on

[6]Note that $a > z_1^a$ can never be an optimal location for the firm, since a marginal decrease in a implies a reduction in distribution costs as well as an increase in market power.

the other hand, on the firm's distribution cost parameters as well as the location of the DC, which alter the degree of convexity of the MRDE.[7] However, the inequality in the best response condition (1) indicates that there may be situations where firm B's location and the set of displacement parameters is such that firm A chooses a corner solution locating at the market edge $a = 0$. Proposition 1 provides conditions which guarantee a best location response inside the market, where MRPD equals MRDE, with a view to the symmetric location choice.

Proposition 1.2.1. *The firm's best location is an interior solution on the Hotelling line if the consumers' travel cost parameter is small enough (relative to the distribution cost parameter).*

In other words, a threshold value t_{crit} determines when the supply-side consideration becomes relevant for the firm's location choice (see Appendix). Let us focus in the following on the interesting case where $t < t_{crit}$.
The effect of the location of the DC on the firm's optimal location response can be broken down into a *local effect* and a *scale effect*.

$$\frac{\partial DC_a}{\partial a} = -\left(\underbrace{2d_1 \cdot (z_1^a - a) + d_2}_{local-effect} \cdot \underbrace{\frac{(z_1^a - a)}{\sqrt{(z_1^a - a)^2 + (z_2^a)^2}}}_{scale-effect} \right)$$

The local effect is the MRDE if the DC is located at the orthogonal projection of the DC on the linear market $(z_1^a, 0)$. This hypothetical location is used to identify the impact of the size of the distribution area which I denote as the scale effect. The scale effect is the part of the MRDE which is determined by the distance of the DC to the market. The latter is especially relevant if we think of logistic centers being located in industrial areas outside the town.[8]

Proposition 1.2.2. *The supply-cost effect on the optimal location response diminishes with the distance of the DC from the market.*

[7] Exemplarily, in Figure 1.3, I set $b = 0,3$ and the set of displacement parameters $(t = d_1 = d_2 = 1)$ with a DC at $(z_1^a, z_2^a) = (0,5; 0,1)$.

[8] An alternative argument would be firms operating in several markets and being supplied by only one DC (not captured in the model).

The further away that the DC is with respect to the market (the shopping area), the smaller the scale effect is and hence the absolute value of the MRDE. This implies that the supply effect on the firm's optimal location choice is most relevant if the DC is not too far from the market. The importance of this result lies in the dependence of the firm's strategic location choice on the scale of its distribution area. Notice that the MRDE is zero when A settles down at the projected location of the DC, i.e., at $a = z_1^a$. However, this would only be an optimal location if we consider only the supply side, ignoring the demand side incentive of product differentiation to create market power. In the following, I solve for the equilibrium considering both, supply and demand side implications of location choice. Considering firms A and B simultaneously yields a system of best responses. To solve for the optimal location choice, as mentioned previously, I distinguish between the situation where the DCs are located inside the market and a more general situation, allowing the DCs to be located outside the market.

Distribution centers inside the market

It is helpful to first consider the case in which the DCs are located somewhere on the Hotelling line. We refer to these as *Market-DCs*, since the DCs are located inside the market such that $z_2^a = z_2^b = 0$. From the optimal location condition as outlined in equation (1), we get a best-response system $BR_a(b), BR_b(a)$ which yields the following polynomial system:

$$a^2\left(-\tfrac{1}{6}t\right) + a\left(-\tfrac{1}{2}t - \tfrac{1}{18}tr - 2d_1\right) + b\left(-\tfrac{1}{6}t + \tfrac{1}{18}tr\right) + b^2\left(\tfrac{1}{18}t\right) + ab\left(\tfrac{1}{9}\right) + \left(2d_1 z_1^a + d_2 - \tfrac{1}{6}tr\right) = 0$$

$$b^2\left(-\tfrac{1}{6}t\right) + b\left(-\tfrac{1}{2}t - \tfrac{1}{18}tr - 2d_1\right) + a\left(-\tfrac{1}{6}t + \tfrac{1}{18}tr\right) + a^2\left(\tfrac{1}{18}t\right) + ab\left(\tfrac{1}{9}\right) + \left(2d_1(r - z_1^b) + d_2 - \tfrac{1}{6}tr\right) = 0$$

We can see from the polynomial structure that, under DC symmetry (i.e., if $z_1^a = r - z_1^b$, which includes the case of a co-located or joint DC at $z_1 = \frac{1}{r}$), we will have a symmetric location solution.[9] In the following, I focus on the symmetric location equilibrium.[10] Solving for the optimal location choice yields the following symmetric and unique Nash equilibrium:

[9] The analytical derivation is provided in the Appendix.

[10] Looking at real retail store locations, which I analyze in Part II, I find that in markets with a strong distribution cost advantage only one chain is active, while in markets where two main supermarket

$$a^*(z,t,d) = b^*(z,t,d) = \begin{cases} 0 & \text{if} \quad t \geq t_{crit}(d,z), \\ \left(12d_1 z_1^a + 6d_2 - tr\right) / (4t + 12d_1) & \text{if} \quad t < t_{crit}(d,z), \end{cases} \tag{1.2}$$

The optimal location choice is characterized by the location of the DCs, captured in the vector z, as well as the displacement cost parameters t and $d = (d_1, d_2)$. Analogous to Proposition 1, we can express the threshold of an interior solution as a critical value of consumers' transportation costs t_{crit} (or as function of the relative importance of transportation and distribution costs captured in $\gamma = t/d_1$, which requires $\gamma < \gamma_{crit} = \frac{12z_1^a+6}{r}$).[11] To summarize, for the union of the set of supply-side parameters and the set of demand-side parameters $\Theta_S \cup \Theta_S$, with

$$\Theta_S = \left\{(z_1^a, d_1, d_2) : z_1^a \in [0,r]; d_1, d_2 \in \Re^+; z_1^a > (tr - 6d_1)/(12d_1)\right\} \text{ and}$$
$$\Theta_D = \left\{(t,r) : t, r \in \Re^+; t < \tfrac{d_1}{r}(12z_1^a + 6)\right\},$$

there exists a unique optimal location choice in the interior of the Hotelling line. This result implies that, when allowing for the coexistence of demand and cost strategies, we can establish interior locations on the product space (contrary to the maximal product differentiation in the standard model, which analyzes the optimal product location only from the demand-side perspective). It is easy to show that, if the DC is sufficiently far from the market edges and $t < t_{crit}$, the optimal location choice of the firm exists and is a unique interior point of the Hotelling line, which solves the trade-off between the MRPD and the MRDE. A special case of an interior solution is the situation where $a = z_1^a$ minimizes the distribution costs.

The result is consistent with standard models. If $t = 0$, such that there is no incentive to differentiate geographically, firms settle down at the location of their DCs to minimize costs ($z_1^a = z_1^b = r/2$ implies Bertrand's equilibrium). The other extreme comprises relatively high transportation costs for consumers. If the travel cost parameter t exceeds the critical threshold, which happens if t is much higher than the

chains are competing the DCs are in general co-located or very close to each other, such that the symmetry assumption of the distribution costs is not too strong.

[11] Alternatively, we could express the existence of an interior equilibrium as a function of a critical $z_1^a(t,d)$.

distribution cost parameter d_1, the demand strategy becomes dominant and firms choose maximal differentiation. Finally, if $d_1 = d_2 = 0$, the optimal location is again that of the d'Aspremont example. Hence, the presence of firms' distribution costs can decrease the degree of product differentiation, which enhances price competition.

Generalization of the DCs' locations

Let us now consider the more general case where firms are supplied from DCs which are allowed to be located outside the market, e.g. in an industrial area or another isolated market. We now distinguish between *Market-DCs* and *Non-Market-DCs*, where the latter refers to DCs which are located off the Hotelling line. Given the location of exogenous DCs and the displacement parameters of consumers and firms, firm A's implicit best response to B's location choice becomes the following:

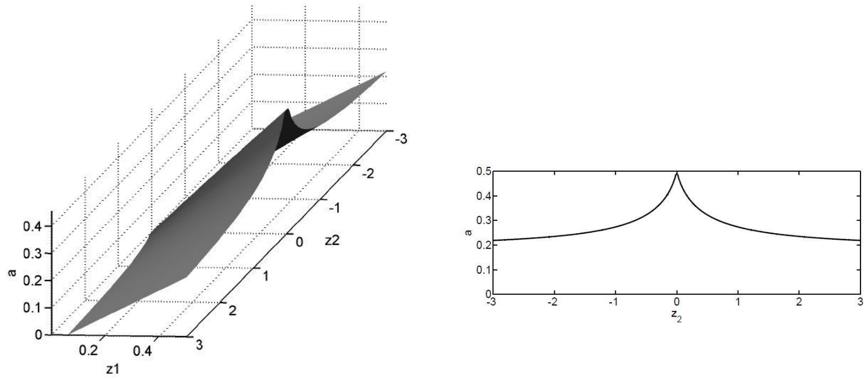
$$a^2\left(-\frac{1}{6}t\right) + a\left(-\frac{1}{2}t - \frac{1}{18}tr\right) + b\left(-\frac{1}{6}t + \frac{1}{18}tr\right) + b^2\left(\frac{1}{18}t\right) + ab\left(\frac{1}{9}\right) + \left(-\frac{1}{6}tr\right) \leq$$
$$-2d_1\left(z_1^a - a\right) - d_2\frac{(z_1^a - a)}{\sqrt{(z_1^a - a)^2 + (z_2^a)^2}}$$

Firm B faces an analogous trade-off. Note that whenever $z_2 \neq 0$ (Non-Market-DC), the MRDEs are no longer linear in a. This is due to the diminishing supply-cost effect as stated in Theorem 2. This implies that the chosen cost specification of the distribution costs is intuitive, but it comes at a cost, namely that the model is no longer analytically solvable. However, focusing on the symmetric case of location choice, i.e., $z_1^a = r - z_1^b$ and $z_2^a = z_2^b = z_2 \in \Re$, the solution can be plotted for any set of displacement parameters (t, d).

Figure 1.4(a) illustrates the dependence of the location choice a on the location of its DC at (z_1^a, z_2^a). Since I focus on the symmetric case, the graph depicts only the market side for firm A (mirrored for firm B). It is easy to verify that, analogous the previous section, the further away that the DC projection $(z_1^a, 0)$ is from the market edge, the larger that a also is. However, and considering the transverse section of the graph, depicted in Figure 1.4(b), note that the effect diminishes in $|z_2|$, i.e., with the distance from the market.

Analogous to the case of Market-DCs, the set of parameters for which an interior solution exists for the general case is defined as follows:

Figure 1.4
Market-DC and Non-Market-DC.



(a) $a(z_1, z_2)$ (b) $a(z_2|z_1 = 0.5)$

$$\Theta^* = \left\{(z, d, t, r) : z_1^a \in [0, r]; d_1, d_2 \in \Re^+; t, r \in \Re^+; \frac{d_2 z_2^a}{\sqrt{(z_1^a)^2 + (z_2^a)^2}} + 2d_1 z_1^a \leq \frac{1}{6} tr\right\}.$$

Although I cannot solve for the general case analytically, the graphical illustration on the one hand confirms the results from the previous section and on the other hand exposes the impact of the size of the distribution area in the location considerations. That is, once firms consider distribution costs in their location decisions, it may no longer be optimal to employ maximal differentiation. However, the distribution economies which drive this result diminish when the distance from the DC to the market becomes great. In other words, the closer that the DC is to the market, the stronger is the trade-off between returns to product differentiation and returns in the form of distribution economies.

Welfare implications

To push the analysis further, I consider the welfare implications when accounting for distribution costs in the optimal location strategy. Maximizing social welfare in the Hotelling framework is equivalent to minimizing costs. However, in the presented model, there are two types of costs. While consumers' transportation costs are minimized at $a^{TC} = b^{TC} = \frac{r}{4}$, distribution costs are minimized at the projected DC location, i.e., at $a^{DC} = b^{DC} = z_1^a = r - z_1^b$. It is easy to deduce that, in the interval $[\frac{r}{4}, z_1^a]$, the social planner will face a trade-off between increasing total transportation costs and decreasing distribution costs (or inversely if $z_1^a < \frac{r}{4}$). In the following, I solve for the social optimum for the case where the DC is located in the market to make it comparable to the closed-form solution provided in Section 2.2.1. The planner faces the following problem,

$$Min\{T(a,b)+D(a,b)\}_{(a,b)}$$

where $T(a,b)$ are the total transportation costs paid by the consumers, i.e., $T(a,b) = \int_0^{\tilde{x}} t(a-x)^2 f(x)dx + \int_{\tilde{x}}^{r} t(r-b-x)^2 f(x)dx$, and $D(a,b)$ are the total distribution costs paid by the firms, so that $D(a,b|z_2=0) = d_1 \cdot \left[(z_1^a-a)^2+(r-b-z_1^b)^2\right] + d_2 \cdot \left[(z_1^a-a)+(r-b-z_1^b)\right]$. Solving for the optimal locations yields the following first-order condition for a,

$$\frac{\partial T(a,b)}{\partial a} + \frac{\partial D(a,b)}{\partial a} = t \cdot \left(a^2 - \left(\frac{r-b-a}{2}\right)^2\right) - d_1 \cdot \left(2z_1^a - 2a\right) - d_2$$

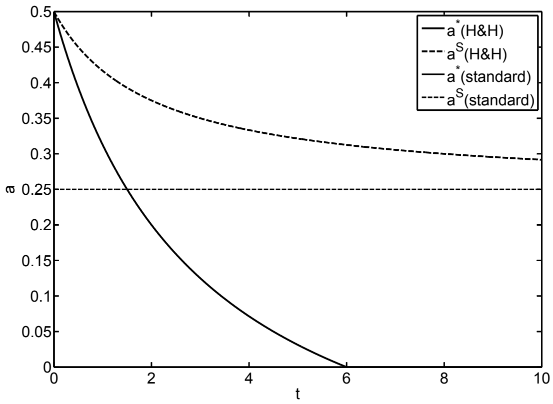
and analogously for b with $r - z_1^b = z_1^a$. Solving for the social optimum, under the coexistence of positive travel costs and positive supply costs, the system yields, after rearrangement, the following social optimal locations:

$$a^{social}_{H\&H}(z,t,d>0) = \frac{0.25tr^2 + 2z_1d_1 + d_2}{2d_1 + tr} \quad \text{and} \quad b^{social}_{H\&H} = r - a^{social}_{H\&H} \tag{1.3}$$

Note that while in the standard Hotelling framework without distribution costs the social optimum is independent of the consumers' transportation cost parameter ($t > 0$), in my model,which internalizes distribution cost effects, the social optimum depends upon the displacement parameters of consumers and firms.

FIGURE 1.5

OPTIMAL MARKET LOCATION AND SOCIAL OPTIMUM (FOR FIRM A).



$\theta_S = (z_1 = 0.5, z_2 = 0, d_1 = 1, d_2 = 0)$.

Moreover, note that $lim_{(d_1,d_2)\to 0}\, a^{social}_{H\&H} = \frac{r}{4}$, which is consistent with the standard

Hotelling setting. On the other hand, $lim_{t \to 0} a^{social}_{H\&H} = z_1 + \frac{d_2}{d_1}$, which minimizes distribution costs. Setting $d_2 = 0$, which imposes quadratic distribution costs (although this is no problem whenever the DC is located inside the market as in the present case), the optimal location is just next to the DC. Finally, comparing the social optimum with the market outcome, I find that the market forces still lead to excessive differentiation, i.e., a gap between the market outcome and the social optimum, but less than in the standard model if the supply cost parameter is sufficiently high relative to the consumers' transportation cost parameter. We briefly illustrate the excessive differentiation (ΔD) as a function of the relative importance of distribution costs and transportation costs, defining $\gamma \equiv t/d_1$ with $t > 0$, $d_1 > 0$. I choose this representation since it reflects the relative importance of the competition effect which is the source of the inefficiency. Since this section considers the case of Market-DCs, without loss of generality I set $d_2 = 0$ and $r = 1$, such that the differentiation gap is given by

$$\Delta D(\gamma, z_1^a) = a^S_{H\&H} - a^*_{H\&H} = \frac{2\gamma^2 + (5 - 4z_1)\gamma}{4\gamma^2 + 20\gamma + 24} \in \begin{cases} [0, \frac{1}{4}] & \text{if} \quad \gamma \leq \bar{\gamma}(z_1^a), \\ [\frac{1}{4}, \frac{1}{2}] & \text{if} \quad \gamma > \bar{\gamma}(z_1^a), \end{cases} \tag{1.4}$$

Consequently, for $\gamma \leq \bar{\gamma}(z_1^a)$, where $\bar{\gamma}(z_1^a) = 2z_1^a + \sqrt{\left(2z_1^a\right)^2 + 6}$, the gap between the social optimal differentiation and the market outcome is smaller than in the standard model. Figure 1.5 illustrated this result and provides, at the same time, a comparison of the market outcome (solid lines) and the social optimum (dashed line) for the 'Hotelling meets Holmes'(H&H)-model and the standard Hotelling model as a function of consumers' transportation costs. Given any distribution cost setting θ_S, the graph shows that the discrepancy between the optimal market location and the social optimum increases in t for interior solutions and decreases if $t \geq t_{crit}$, where the firm chooses a corner solution. Within the limit ($t \to \infty$), the supply effect is dominated by the competition effect and we are back at the standard model.

1.2.3 Robustness check: the effect of DCs on variable costs

We have considered distribution costs as fixed costs within a firm's profit function. However, distribution costs may be 'passed on' to consumers if we allow them to also effect the variable costs.[12] Hence, let us consider, in addition to the fixed distribution costs as specified in the previous section, the variable costs of firm A such that they increase with the distance of the firm to its DC, i.e., $c_a(|z_a - a|)$ with $\frac{\partial c_a}{\partial |z_a - a|} \geq 0$. Analog for firm B. For demonstration purposes, let us assume the functional form $c_a = \alpha \cdot |z_a - a|$ with $\alpha \geq 0$, set $d_2 = 0$ and $r = 1$, and solve by backwards induction for the symmetric equilibrium ($z_b = 1 - z_a$). The optimal location choice of firm A also now depends upon the parameter of the variable costs α, as follows:

$$a^*(z, t, d, \alpha) = b^*(z, t, d, \alpha) = \begin{cases} 0 & \text{if} \quad t \geq t_{crit}(d, z, \alpha), \\ \left(12 d_1 z_1^a - t + 5\alpha\right) / (4t + 12 d_1) & \text{if} \quad t < t_{crit}(d, z, \alpha), \end{cases}$$

In equilibrium, an interior solution as well as a corner solution is possible, which depends again upon the transportation cost parameter for consumers. Comparing this model variation with the result in equation (2), note that t_{crit} increases, which relaxes the condition to achieve an interior solution. In other words, if locating closer to the distribution facilities not only implies savings on the fixed costs of the firm but also decreases marginal costs ($\alpha > 0$), then an interior solution is even easier to achieve.

1.3 An application to the location of supermarkets

In this section, I aim to verify the impact of distribution costs on firms' geographic differentiation empirically for a particular example of a distribution-intensive industry. I consider the leading conventional supermarket chains in the US, namely Kroger Co. and Safeway Inc., both market-listed and operating predominantly as 'neighborhood grocery stores'. With focus on the trade-off between differentiation from competitors and distribution economies, I have chosen competitors which are on a par with each other and abstract from the competitive pressure of mass merchandisers, like Wal-Mart, on traditional supermarkets (see, for example, Jia, 2008, or Matsa, 2011).[13]

[12]For a detailed discussion on 'cost pass-on', depending upon the market structure and type of competition, you may consider Stennek and Verboven (2001).

[13]Originally, I considered also the big box chains Wal-Mart and Target but, in contrast to the neighborhood stores of Kroger and Safeway, I find that these chains are not operating in the same geographic

I also abstract from a possible trade-off between differentiation and agglomeration as considered by Datta and Sudhir (2011). I present first the data and the measure of differentiation, and subsequently use a multivariate regression analysis to verify whether the presented model offers a valid explanation for the firm's behaviour revealed through the observed location choice.

1.3.1 Data

I use data on supermarket locations in the US for Kroger and Safeway. All the store locations have been identified from POI datasets.[14] The advantage of this type of data source is that locations are already geo-codified, which avoids matching problems with a manual geo-codification (which would be necessary to measure efficiently the geographic differentiation between a huge number of stores). Additional information from the respective firms' websites allows the identification of the store format which operates under a certain banner and the location of the regional DCs. Moreover stakeholder information, especially the 'Fact Book' and 'Annual Report', allows the verification of the consistency of the POI data, which turns out to be highly accurate. The differences in the number of stores indicated by the POI dataset and the official financial publications are three stores for Kroger and 24 stores for Safeway. Both are small deviations with respect to the total number of stores of the chains. The difference is assigned to the time difference in the data collection for the POI dataset and the corporate financial information. More detailed comments on the data are provided in the appendix.

For the spatial analysis, in particular the calculation of geographic distances, I use the Geographic Information System ArcGIS. Based on freely available polygon-shape files for different spatial units in the US with associated demographic characteristics, I define reasonable geographic markets and construct the following cross-sectional

markets or else the markets would have to be defined as extremely large such that, assuming consumers travel within such a large geographic area to purchase fresh grocery products, it becomes implausible in terms of irrational travel distances. The data indicate that only 67% of Wal-Mart's stores are located in urban areas, while Target operates 81% of its stores in urban regions.

[14]POI stands for 'Point of Interest', an expression from GPS technology in which these datasets are used to provide GPS customers of any brand with an update of locations which might be of interest to them when on the road. Some common examples of POIs other than supermarkets are hospitals, speed cameras or gas stations.

datasets:

$$Markets = \left\{ Pop_m, HH_m, SQMI_m, N_m^K, N_m^S, Dist\_centroid_m^{DC,j} \right\}$$

$$Stores = \left\{ X_s, Y_s, Diffs_s^{comp}; Pop_{msj}, HH_{msj}, SQMI_{msj}, N_m^{own}, N_m^{comp}, Dist_{ms}^{DC,own} \right\}$$

The first dataset-type consists of market-level data. The observations comprise the markets, indexed by 'm', where at least one supermarket chain is active, associated variables like the number of stores per chain in each market (N_m^K for Kroger and N_m^S for Safeway), the population and the number of households per market (Pop_m, HH_m), the geographic market size in square miles ($SQMI_m$) and the distance from the market centroid to the closest regional DC of each firm ($Dist\_centroid_m^{DC,j}$).
The second dataset consists of store-level data and associated market data for a particular store *s*. The store data have been constructed using a vertical combination of the store dataset for each firm. The final dataset contains the projected store locations (X_s, Y_s), the distance from each store to the closest regional DC of the relevant chain affiliation ($Dist_{ms}^{DC,own}$), and the distance to the closest competitor store within a market ($Diffs_s^{comp}$). The associated market features are as in the market-level data.

1.3.2 Descriptive proximity analysis

In total, Kroger counts 2.110 and Safeway 1.487 supermarket stores. Since I am interested in each firms' location choice inside a market, I need to define reasonable shopping areas to identify where the stores compete. In the literature based on Bresnahan and Reiss (1990), markets are usually defined as isolated cities. Recently, Ellickson et al.(2011) proposed a variation where this assumption is relaxed, allowing for market spillover effects for metropolitan and micropolitan areas, but I find that this market definition is too broad to be considered a shopping area for fresh grocery products. Instead, I looked for a market area definition such that consumers can be assumed to move within this area for grocery shopping given the data-availability constraints of the demographic and geographic market characteristics.[15] I propose 'urban areas' (UAs), densely-settled census-block groups that meet a minimum population density,

[15]This is in line with the geographic market definition by the European Commission, which defines a retail market for daily consumer goods as "the boundaries of a territory where the outlets can be reached easily by consumers (radius of approximately 20 to 30 minutes driving time)" (COMP/M.5112 REWE/PLUS par.18, 2008).

as natural shopping areas for neighborhood supermarkets. To the best of my knowledge, this definition has not been used so far in this context, but the statistics show that this market definition captures almost all supermarkets in the data and yields reasonable travel dimensions for grocery products. I find that approximately 90 % of all the neighborhood stores of the two considered chains are located in UAs, which is taken as evidence of a natural shopping area for this type of store. To illustrate where these markets are located, the appendix provides a map of the markets considered.

Table 1.1
Summary statistics.

	Kroger	Safeway
Summary:		
Total number of stores in UAs [% Total]	1,870 [89%]	1,373 (92%)
Markets (UAs)	437	280
Markets with at least 2 stores of either of the chains	160	180
Duopoly markets (both firms active)	67	67
Total number of Regional DCs	25	12
Proximity Measures:		
All markets		
E[Distance to closest own store]	2.82 (1.95)	2.68 (1.87)
E[Distance to closest DC]	68.59 (71.79)	57.20 (58.09)
E[number of stores in a market]	4.28 (12.70)	4.90 (13.67)
Duopoly markets		
E[Distance to closest own store |Competition]	2.57 (2.03)	2.08 (1.97)
E[Distance to closest competitor|Competition]	1.96 (1.89)	1.96 (1.89)
E[Distance to closest DC|Competition]	30.96 (42.33)	44.13 (51.30)
E[number of stores in a market|Competition]	10.21 (24.53)	10.21 (20.97)
Average Market Characteristics:		
E[Population in a market]	183,742 (738,431)	337,681 (1,470,633)
E[Number of Households in a market]	68,292 (256,462)	122,381 (525,735)
E[Geographic market size (in sq. miles)]	72 (198)	94 (321)

*Standard deviations in round brackets.

Table 1.1 provides a summary of the variables that will be used in the following analysis. Considering the continental United States, Kroger, as the leading supermarket chain, operates in more markets than Safeway and counts more DCs. This observation is not surprising since, being active within a larger geographical space, its markets are organized in more distribution areas. However, the statistics show that the two main supermarket chains target similar markets. The data even suggest that their strategic entry decision is statistically equal in markets where they compete with each other (which I indicate in the statistics with the condition 'Competition').[16]

Section two of the summary statistics provides several proximity measures - the expected distances between stores of the same chain to competitors and to the closest DC which supplies a given chain. All the distances are measured in Euclidean distances in miles.

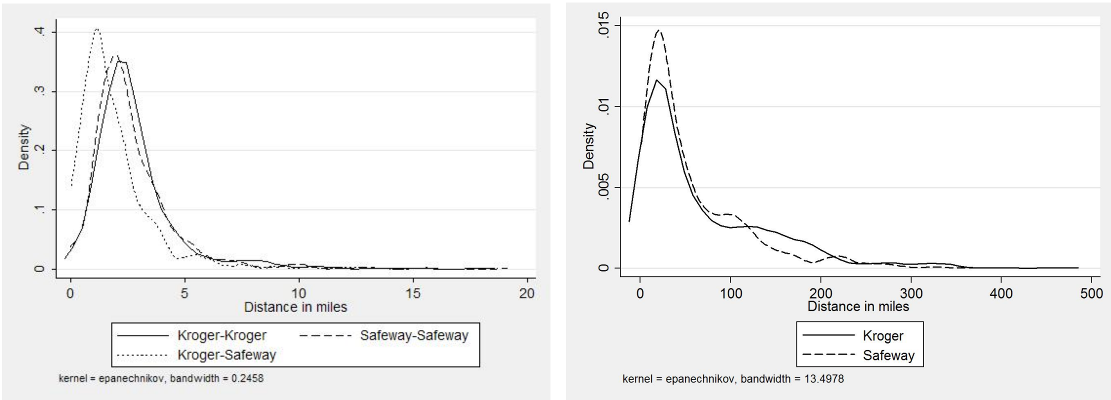
Comparing the two main supermarket chains, on average, the distance between two Kroger (Safeway) stores within the same geographic market is 2.5 (2.0) miles, while the average distance with respect to the closest store of the competitor is 1.9 miles.[17] Taking into account that Safeway indicates to draw on average customers from a 2.0-2.5 mile radius, the average distance between competitors suggests the existence of overlapping market areas between the rivals (analog the 'competitive areas' from the extended Hotelling model). Additionally, it calls attention that in the presence of competition both firms in question face a smaller average distribution distance than in 'monopolistic' markets.[18] This difference is more pronounced for Kroger than for Safeway, with Kroger facing in competitive markets an average distance of 30 miles to its regional DC compared to 68 miles in 'monopolistic' markets. At this point you may argue that the markets close to DCs may be more attractive or that DCs, which are often located in industrial areas, are more likely to be located close to large markets where competition is more likely. We will have a detailed look at markets with competition in order to study whether the joint consideration of supply and demand in the location choice of the firms may partially explain these observations.

[16] I abstract from scale effects, which might be larger for Kroger as the leading supermarket chain.

[17] Considering only markets where both firms are present, the average distance between the firm's own stores becomes even smaller which may suggest an intent of pre-emptive behaviour of the firm, e.g., packing stores close together to foreclose the market, but since we are interested in the spatial differentiation with respect to the rival we don't consider this aspect in the present paper.

[18] In this context I use the term 'monopolistic' for markets where only one of the two firms in question is present.

FIGURE 1.6
DISTANCE DISTRIBUTIONS.



(a) Differentiation (b) Supply-Distance

Figure 1.6 illustrates the distribution of the distance variables in more detail. Note that the own-store differentiation of both supermarket chains follows a very similar pattern. The same holds for the differentiation with competitors in those markets where both chains are active, though with a shift to the left which reflects the lower expected differentiation compared to the closest firm's own store. Considering the distribution of the supply distance, both firms show a mode of around 30 miles, with a flat tail from mile 200. I interpret this pattern as a potential colonization pattern of stores close to DCs. Furthermore, the data let us suspect that there is a kind of threshold region before the distance becomes so large that the DC is considered as inaccessible.

1.3.3 Empirical analysis of supply-distance effects

In order to verify whether the proposed mechanism suggested by the model yields a possible explanation for the observed pattern in the data, I run an empirical analysis using continuous distance measures. The variable of interest is the geographical differentiation between a store of chain i and a store of chain j, denoted as $Diff^{comp}$, which is estimated as a function of demand shifters (X) and distribution aspects from the supply side (Y).

$$E\left[Diff^{comp}|X, Y\right]$$

Recall that the constructed datasets of stores and markets, where at least one store per market is active, captures thee possible market outcomes in terms of the market presence of the supermarket chains. To verify if the proposed theoretical model can provide a possible explanation for the observed pattern in the data, we select only markets with competition, i.e. markets with $N^K \geq 1, N^S \geq 1$. Since the selection rule is a deterministic function of the market presence, which is captured in the matrix X, the selection issue can be ignored.
As such, let us specify the model of geographic differentiation,

$$E\left[Diff^{comp}|X, Y\right] = \beta_0 + \beta_1 X + \beta_2 Y$$

$$\text{with } X = \left(Pop, SQMI, N^{own}, N^{comp}\right)' \quad \text{and} \quad Y = \left(Dist^{DC,own}, (Dist^{DC,own})^2\right)'$$

The underlying intuition of this specification is based on the H&H model presented in the previous chapter. Note that, if the DC costs are not considered in the firm's location choice, the spatial differentiation with respect to the competitor should be independent of the distribution distance. I expect that, if the DC is not too far away from the market, the stores consider the distribution distance in their location choice with respect to their competitors. However, when bringing the model to the data, I face three potential problems which are discussed in the following.

Network problem. The ideal experiment to analyze whether there is a distribution effect as specified in the model would be to take otherwise equal linear cities with $N = 2$ stores each and random DC locations in space. However, contrary to the simplified theoretical model, in the real world there are markets with more than two stores, i.e., a store network for which our linear model does not account. In such markets, a supermarket has to consider the geographic differentiation with more than one competing store. It seems reasonable that the closest store, in terms of the Euclidean distance, matters most in the price competition, but considering only the 'closest neighbor' ignores possible competition effects of other stores.[19]

[19] A related problem arises for markets where A is the closest neighbor of B but where for A the closest neighbor is C.

Simultaneity problem. The aim is to explain the store-differentiation as a function of the location of the closest DC. If I use the distance to the closest DC as an explanatory variable, I may introduce a simultaneity problem. If the distribution distance is endogenously determined by the store's location choice, which is captured in the differentiation of the firms, the estimated coefficient β_2 will be biased.

As a first step, to demonstrate the link between the geographic differentiation and the distribution distance, I run an *ad hoc* analysis using the closest neighbor distances as the dependent variable and the store distance to the closest DC as an explanatory variable.
As the second step, I address both of the above-mentioned problems at once using aggregated data. To address the network problem, the easiest solution to implement is to redefine the dependent variable as the average differentiation within a market. This might be interpreted as a kind of representative differentiation within a market, but it comes at the cost of 'losing' observations when going from store-level data over to market-level data. For the analysis of the store differentiation with the closest competitor, we are left with 67 observations (duopoly markets). For the purpose of this analysis, I consider this small sample as still sufficient to eliminate the network problem at low cost.[20] Hence, I implement the solution with aggregated data and address the potential simultaneity problem of the distribution distance with an IV approach, using the distance to the firm's exogenous DC location to the market centroid ($Dist\_centroid^{DC}$) as instrument for the distance to the closest DC. The distance to the market centroid is highly correlated with the store distance to the DC, and is supposed to affect the differentiation between stores only through the store distance to the distribution center and therefore can be considered as exogenous, such that the it provides a valid instrument for the distribution distance. Since I include level as well as squared distribution distances, I use both the distance and the squared distance from the market centroid to the closest DC, which are linearly independent instruments.

[20] A more sophisticated solution, using store-level data, would be to redefine nearness, taking the weighted average differentiation over an x-miles radius around each store or to set up a structural model. (For a discussion of "What is near?" see, for example, Miller(2004).) For both solutions, we need a detailed geography setup which goes beyond the purpose of this paper.

TABLE 1.2
REGRESSION RESULTS.

	Kroger	Safeway
Panel A	Store level - coefficient estimates	
Population (in 100T)	-0.02047***	-0.01015**
Sqmi	0.00160***	0.00046***
$N^{Kroger} = \{1, 2, ..., 10, 10^{+}\}$	0.27559***	-0.56419***
$N^{Safeway} = \{1, 2, ..., 10, 10^{+}\}$	-0.36954***	0.62319***
$Dist^{DC}$ (in 100 miles)	-0.95976**	0.08477
$(Dist^{DC})^2$	0.34582**	0.00189
cons	2.42450***	1.332342***
Panel B	Market level - coefficient estimates	
Population (in 100T)	0.01797	0.04977$^{(*)}$
Sqmi	0.00273**	0.00183$^{(*)}$
$N^{Kroger} = \{1, 2, ..., 10, 10^{+}\}$	-0.01569	-0.07802***
$N^{Safeway} = \{1, 2, ..., 10, 10^{+}\}$	-0.04202**	0.0217634
$E[Dist^{DC}]$ (in 100 miles)	-1.86810***	-1.87496***
$E[Dist^{DC}]^2$	0.5346217***	0.67567***
cons	2.48834***	2.53548***

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level and $^{(*)}$Significant at 12% level by reason of small sample properties; Instrumented variables: $E[Dist^{DC}], E[Dist^{DC}]^2$, Instruments: $Dist\_centroid^{DC}, (Dist\_centroid^{DC})^2$ and the respective exogenous explanatory variables.

Table 1.2, Panel A, presents the results of the *ad hoc* analysis based on store-level data, with the geographic differentiation of Kroger (Safeway) from competing stores as the dependent variable. Note that, additional to the problems that have been discussed in the previous paragraph, the market structure in terms of the number of stores of each chain is endogenous, i.e. more stores in a small area necessarily causes a smaller store-differentiation and a smaller store-differentiation implies smaller market shares for each store such that we will have more stores in the market. Since this is just a preliminary regression and the aim of the empirical analysis is not to explain market entry, let us ignore this fact assuming the number of stores as exogenous in the location choice and focus on the effect of the distribution distance. Looking at the results for Kroger, the distribution distance is significant in its location choice, while for Safeway it is not. Notwithstanding the summary statistics suggest that the firms follow similar strategies. As outlined previously, this regression is subject to a potential simultaneity problem between the distribution distance and the spatial differentiation to the competitor (if our theory is true) such that the estimates are potentially biased. Interpreting these results, we may conclude that only Kroger internalizes the distribution costs. However, we will see that this conclusion, based on the biased estimates, is misleading.

Let us now consider Table 1.2, Panel B, which presents the market-level regressions with instrumented distribution distances. Note that now for both firms the (level) distribution distance has a significant negative effect. Moreover the significant quadratic terms in both regressions suggest a U-shaped pattern of the distance to the DC. Together with the negative coefficient of the level distance and the positive intercept, the quadratic pattern implies that for 'small' supply distances the differentiation decreases with the supply distance, while for large distances the differentiation increases. For Kroger, the average minimum differentiation is reached at 174 miles and for Safeway at 138 miles respectively, which is in line with our conjecture about a kind of distance threshold when interpreting the distribution of the supply distance in Figure 1.6. With respect to the model, the results suggest that both firms are playing a hybrid location strategy, considering distribution costs in its strategic positioning as outlined in the simple linear model with distribution costs. If the DC is more than 174 (or 138) miles away, a store differentiates more and more from its competitor, since distribution economies become less important (which is in line with the extension of the Hotelling model when $z_2 > 0$). Respective other location determinants, we find that the size of the market area increases the differentiation between rival stores, which is not surprising given that in a larger market there is more room for differentiation. We do not find any significant population effect. Assuming a uniform population distribution within the market, this is in line with the standard Hotelling model (which doesn't allow for capacity constraints). Last, but not least, we find a significant negative effect of the number of the rival's stores in the market. This result suggests that retail chains do not cluster own stores together but interlace their stores with the stores of the rival such that more rival stores imply less differentiation possibilities.

To summarize, the data suggest that, for close DCs, the differentiation decreases with the distribution distance, while for sufficiently distant DCs, the differentiation between firms increases, which can be justified by our extension of the Hotelling model introducing distribution costs. The significant distribution effect is also related with the empirical results of Matsa (2009), who shows that product availability in terms of low stock-out rates, which decrease with distance to suppliers, are important to maintain competitiveness.

Finally, note that a limitation of this application is that we abstract from other grocery retailers. We may think of other supermarkets and alternatives like fresh stores, organic food stores or small-format value-priced stores that may have an impact on the differentiation between the two main conventional supermarkets. Ignoring grocery retailers that ar not on a par with the firms in question, I assume implicitly 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 such that the most important rival for Safeway, who can steal a significant part of its consumers, is Kroger and vice versa.

For further empirical analysis of the location choice of Safeway and Kroger, I refer to my second thesis chaper, which models the location choice as a discrete game (in contrast to the continuous regression model presented in this paper).

1.4 Discussion: alternative applications of the model

We can think of other applications of the extended version of the Hotelling model. First at all, let us consider two service stations locating on a highway (the market) with the locations of consumers being the kilometer mark when the fuel light goes on, which can be assumed to be uniformly distributed over the highway and drivers can stop at a service station at any time. In this setting, the DC can either be interpreted as an industrial area with the logistics centers of the service stations (on the highway or ’outside’, i.e., on any other highway), or as the location of a city, close to or apart from the highway, with the residences of potential employees and a labor supply decreasing with distance such that the wage rate increases with distance and consequently the costs of the firms. In any case, our model suggests that a maximal differentiation (i.e., locating just after the motorway approach and just before the motorway exit) may not be optimal if the service stations endogenize the fixed (labor or/and distribution) costs.

So far, I have referred to differentiation as the geographic distance between firms, but the presented mechanism can be transferred to further problems of product differentiation, in particular the decision of product design. Let us redefine the middle of the line segment as a basic product which can be produced with the common knowledge exhibited within the industry. Assume that any further development of the product characteristics (e.g. tailoring to a specific consumer group) requires specific knowledge which comes at a fixed cost that increases with specialization. In this context, the 'DC location' is the generic product and the 'distribution distance' comprises the development costs of more specialized products. The implication of a hybrid location strategy is that the specialization cost can lead start-up firms to choose more generic products compared to the case where specialization costs remain unconsidered in the product decision. Alternatively, we may think of two firms being endowed ex-ante with a particular technology (incumbent product) and having to decide whether to develop it further in order to optimize their location in the product space. Some concrete examples may be found in the software and automobile industries, both industries involving labour-intensive and complex development processes that require specialized skills. For instance, for software vendors, it may be more efficient to sell relatively generic software packages at competitive prices rather than more specialized software solutions that imply high development costs. In the automobile industry, we may think of a particular car model of each manufacturer and each of their decisions about the new generation of cars, i.e., how far away the engineers move from the characteristics of the original model. In other words, if the fixed R&D costs are internalized in the product design decision, the cost consideration can change the optimal location in the product space relative to a pure demand-based decision.

1.5 Conclusion

A theoretical model has been provided along with empirical evidence to explain how the consideration of operational efficiency, in terms of supply costs, in firms' optimal location choices affects the degree of product differentiation among firms. The proposed model has shown that, by internalizing the firms' distribution costs in an otherwise standard Hotelling framework, the maximal horizontal differentiation of competing stores might no longer be optimal. Under weak conditions on the displacement parameters, the trade-off between demand and cost considerations in the firms' hybrid location choice induces an optimal location in the interior of the market. Although firms earn less marginal revenues due to increased price competition, in terms of net profits they are better off than they would be were they to ignore distribution economies and treat supply costs as exogenous once they are established. However, and also, consumers benefit from the hybrid location strategy of the firms since they face lower prices and incur lower (or equal) aggregate transportation costs compared to the standard model. The empirical verification of the model for optimal supermarket locations suggests that supermarket chains consider distribution distances in their location choices. The optimal degree of geographic differentiation to the competitor depending on the distance to the closest DC is U-shaped, declining for small or moderate distribution distances and increasing for long distances. The result is in line with the theoretical model, suggesting that a hybrid location strategy is profit-maximizing.

The theory and the empirical data suggest that the trade-off between competition effects and distribution economies is strongest when the distribution facility is relatively close to the market where the stores are operating. If the DC is too far away, the distribution economies decrease and the competition effect dominates the degree of product differentiation.

This paper is a first step for a better understanding of firms' optimal location choices in distribution-intensive industries and provides incentives for further empirical research on the identification of location strategies.

1.A Appendix: Proofs and algebraic details

Symmetric solution of location choice. We can either see it directly from the best response function or solve for it analytically if we subtract $BR^1_a - BR^1_b$ and solve the quadratic equation under the feasibility constraint:

$$\left(a^2 - b^2\right) * \left(-\tfrac{2}{9}t\right) + (a-b)\left(-\tfrac{1}{3}t - \tfrac{1}{9}tr - 2d_1\right) \leq 2d_1\left(r - z^b_1 - z^a_1\right)$$

Define $\gamma \equiv \frac{t}{d}$ and $\bar{z} = \frac{z^a_1 + z^b_1}{2}$, then

$$a(b) = \begin{cases} b & \text{if} \quad z^a_1 = r - z^b_1 \left(\Leftrightarrow \bar{z}_1 = \frac{1}{2}\right), \\ -1 - 9/(2\gamma) + \sqrt{[b + 1 + 9/(2\gamma)]^2 + (9/\gamma)(2\bar{z}_1 - r)} & \text{otherwise} \end{cases}$$

In this paper, I focus on the symmetric location equilibrium, but I might conjecture that whenever the symmetry condition $z^a = r - z^b$ does not hold, there exists an asymmetric location equilibrium iff the cost advantage of the market leader is not too strong.

General DC location. Under symmetry, the optimal location is implicitly given by $F = a\left(-\frac{2}{3}t - 2d_1\right) + d_2 \cdot \frac{1}{\sqrt{1+\left(\frac{z_2}{z_1 - a}\right)^2}} - \frac{1}{6}tr + 2d_1 z_1 \leq 0$. Since $F(a = -\infty) = -\infty$ and $F(a = +\infty) = +\infty$ and F is continuous in a, there is at least one root. Moreover, since all the summands of F are monotonic on the interval $[0, r]$ or else constant, the root is also unique. To check whether there is an interior solution on the Hotelling line, it is enough to check for a positive root, which is the case whenever $F(0) > 0$. Evaluating F at zero yields the following condition for an interior solution: $\frac{d_2 z_2}{\sqrt{z_1 + z_2}} + 2d_1 z_1 \leq \frac{1}{6}tr$.

Proof Proposition 1. The firm's best location is an interior solution on the Hotelling line if the consumers' travel cost parameter is small enough (relative to the distribution-cost parameter) such that $t < t_{crit}(b) = \left[2d_1 z^a_1 + \frac{d_2 z^a_1}{\sqrt{(z^a_1)^2 + (z^a_2)^2}}\right]\left[-\frac{1}{18}b^2 + \left(\frac{1}{6} - \frac{1}{18}r\right)b + \frac{1}{6}r\right]^{-1}$.
Under symmetry, the condition collapses to $t < t_{crit} = \frac{1}{r}\left(12d_1 z^a_1 + \frac{6d_2 z^a_1}{\sqrt{(z^a_1)^2 + (z^a_2)^2}}\right)$.
Since for $z_1 > a$ the MRDE(a) are strictly increasing in a and MRPD(a) are strictly decreasing in a, if $MRDE(a = 0) > MRPD(a = 0)$ the firm chooses a corner solution, $a = 0$. From the equilibrium condition (1), it can be seen that this is the case whenever

$\left(\frac{1}{18}t\right)b^2 + \left(\frac{1}{18}tr - \frac{1}{6}t\right)b - \frac{1}{6}tr < -2d_1z_1 - \frac{d_2z_1}{\sqrt{z_1^2+z_2^2}}$, and under rearrangement we can establish a critical value $t_{crit}(b; z, t, d)$. If $t > t_{crit}$, the demand effect dominates the supply effect and the firm finds it optimal to choose maximal differentiation. Note that, if $z_2 = 0$, $d_2 = 0$ or $d_1 = d_2$, I could define a relative threshold $(t/d_1)_{crit.}$. Under symmetry $a = b$, the threshold reduces to $t_{crit} = \frac{1}{r}\left(12d_1z_1 + \frac{6d_2z_1}{\sqrt{z_1^2+z_2^2}}\right)$.

Proof of Proposition 2. First, recall that the effect of the market distance from the exogenous DC location is linearly separable from the market events, i.e., the hypothetical case where agents as well as DCs are located inside the market. Hence, I take the derivative of the *scale effect* with respect to the distance between the market and the DC's location (z_2):

$$\frac{\partial^2 DC_a}{\partial a \partial z_2^a} = \frac{d_2(z_1^a - a)z_2^a}{[(z_1^a-a)^2+(z_2^a)^2]^{\frac{2}{3}}} \geq 0 \quad for \quad z_1^a \geq a$$

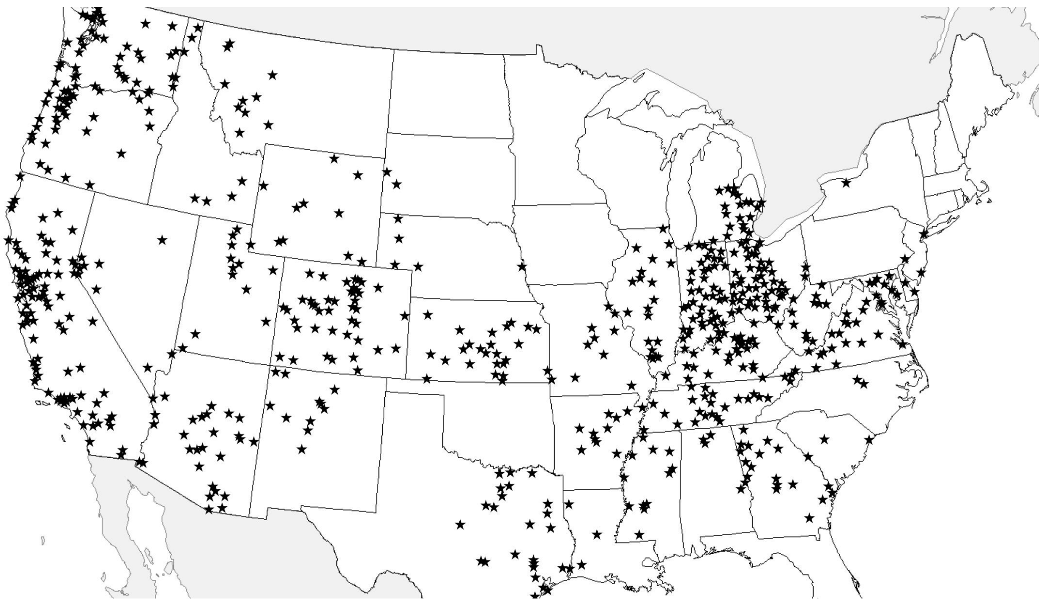
Since the MRDEs are negative for any $z_1^a > a$ (indicating marginal cost-savings), the positive sign of the second derivative implies diminishing distribution economies as the distance of the DC to the market becomes large.

1.B Appendix: Detailed explanation of the data

Kroger. To identify supermarkets which are operated by The Kroger Company, I use a free POI file from July 2012 identifying the geographic coordinates and banners for all grocery stores which are under the firm's ownership (www.poi-factory.com). Additional information from the firm's website allows us to identify the store format operating under each banner (www.thekrogerco.com). The GPS data provide a total of 2.428 grocery retail stores in the US, of which 2.110 are supermarkets, 146 are warehouse stores and 172 are multi-department stores (similar to super-centers). The data are consistent with the firm's public information, indicating in May 2012 a total number of 2.425 grocery retail stores, i.e., three stores less than the data which I assign to the two-month difference between these data sources. (The data consistency holds also for the firm's convenience stores, which differ by only three stores, with 786 stores registered in the POI dataset and 789 stores indicated by the firm in May 2012.) The locations of the distribution facilities are collected from the firm's 'Ship-to Warehouse Location List' for vendors, who are required to use an EDI (Electronic Data Interchange). In 2012, the warehouse location list indicated 34 distribution divisions of which 27 are local distribution divisions and seven are supra-regional consolidation warehouses, denominated 'Peyton's DC' and 'Goddard Western DC'. While some divisions have only one big local DC, others have several specialized warehouses located next to each other; in the latter case, I took the street address of the most general one for the geo-codification. The information is consistent with other firm's sources, such as the '2011 Fact Book', which indicates 34 DCs. It is worth mentioning that some DCs are operated by the firm itself while others are operated by third-party service providers, which is as a result of Kroger's outsourcing and remodeling of its distribution network during recent years. When analyzing the sub-sample of the supermarket format only, I exclude the FredMeyer Regional DC (division 22) which supplies the multi-department stores that are operated under this banner.

Safeway. To identify the stores and DCs of Safeway, I use two types of sources. First, I use a POI dataset which identifies all Safeway facilities in the US and Canada based on the firm's own information. The dataset provides locations for all stores of any brand as well as associated DCs operating in March 2008. After sorting out the number of retail stores in the US, we are left with 1.545 store locations in the US, of which 973 are operated under the Safeway banner, 300 Vons, 116 Randalls, 80 Dominick's, 37 Genuardi's and 39 Carrs (I eliminate one observation 'Citrine Bistro'). A comparison with data from the 'SW Fact Book 2008' and the '2007 Annual Report' shows an acceptable difference of 24 stores. The US stores are assigned to nine operational areas (divisions) which are supplied by 13 main DCs. In general, each division has one regional DC, the exceptions being South California (Vons) and Texas (Randalls), which have two DCs each, and Seattle which is supplied by three different DCs. Complementary information from the firm's website allows us to match each store with its corresponding DC by division.

Market definition. Markets for 'neighborhood grocery stores' are defined as UAs. We have shown that this particular definition is convenient for the Kroger/Safeway data. To illustrate where these markets are located, the map below indicates all the UAs where at least one of the firms is present.



Considered markets (UAs) in the US with active Kroger stores and/or Safeway stores.

CHAPTER 2

The role of captive consumers in retailers' location choices

2.1 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 supermarket 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 á 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.

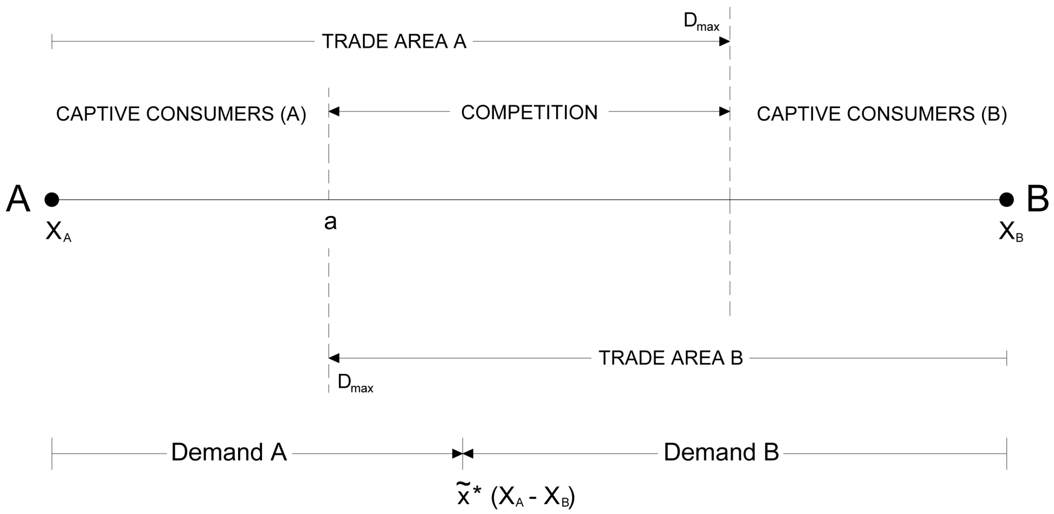
2.2 Economic intuition

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 2.2.1 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.

Figure 2.2.1
Stylized price setting under spatial differentiation and fixed trade areas.



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 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, I transfer 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.

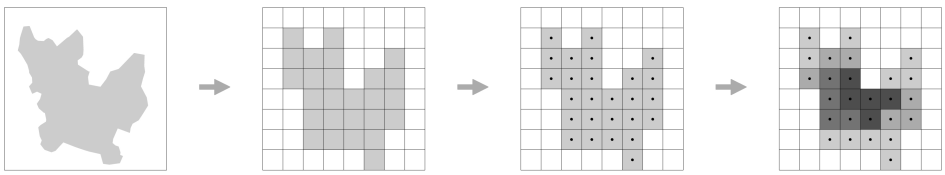
2.3 An econometric spatial location-price game

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.

2.3.1 The model

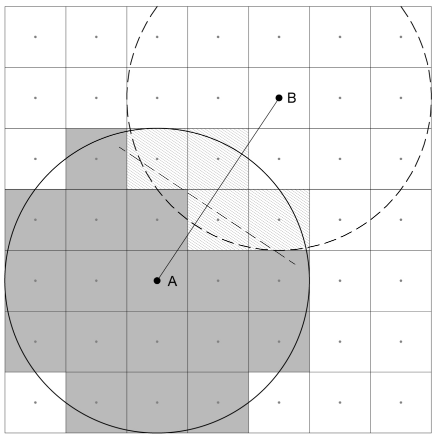
Consider a spatial market m of any polynomial shape with a finite number of equally-spaced discrete locations L_m and a corresponding discrete consumer distribution $F_m(X)$, as illustrated in Figure 2.3.2.

FIGURE 2.3.2
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.[21] 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 2.3.3 illustrates the most interesting case of differentiation with captive consumers.

Figure 2.3.3
Price competition and market power in space.



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

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

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 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 $l = \{1, 2, ..., L_m\}$ is defined as follows: [22]

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

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 competitive 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.

[22] The 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.

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.

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

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 $\Delta Captive_{Fl}$. Omitting again the market subscript, the expected profit of specification (I) and (II), respectively, is

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

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

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

$$BP^F_l = \Psi^F_l(BP^{-F}, X, Z; \beta, \delta) \quad \forall l$$
$$BP^{-F}_l = \Psi^{-F}_l(BP^F, X, Z; \beta, \delta) \quad \forall l$$

where Ψ^F_l 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:

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

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

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

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

2.3.2 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.

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, Agguirregabiria 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 nests 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. [23]

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).[24] 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:

$$Max_{\left(\beta,\delta,\{BP^F_m, BP^{-F}_m\}^M_{m=1}\right)} \quad \sum_{m=1}^{M} \sum_{l\in\mathcal{L}_m} \left[d_{mFl} \cdot log(BP^F_{ml}) + d_{m-Fl} \cdot log(BP^{-F}_{ml}) \right]$$

s.t.

$$BP^F_{ml} = \Psi^F_{ml}(BP^{-F}, X, Z; \beta, \delta) \quad \forall l, m$$

[23] Although 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.

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

$$BP_{ml}^{-F} = \Psi_{ml}^{-F}(BP^F, X, Z; \beta, \delta) \quad \forall l, m$$

$$0 \leq BP_{ml}^{F} \leq 1 \quad \forall l, m, F$$

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.

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.[25] 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 multi-

[25] Zhu 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.

ple 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 structural 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.

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.

2.4 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 border-line 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.[26]

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 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.[27] 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.[28] Next, I define the centroids of the cells as possible

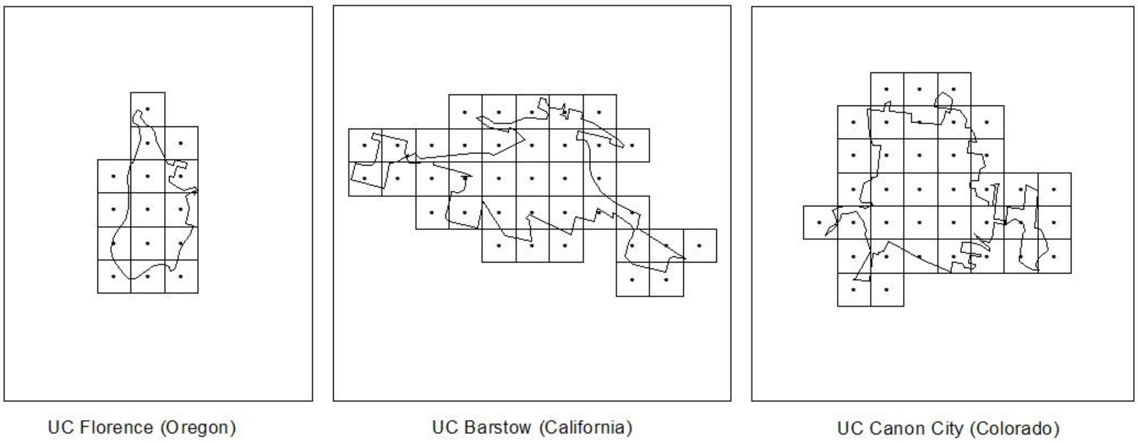
[26]Note that the construction of the variables rest on the definition of the exogenous radius of influence. Since this is the case in most of the empirical spatial competition models, and since for a small perturbation of the radius I do not expect any change in the conclusions, I rely upon the information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

[27]By '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.

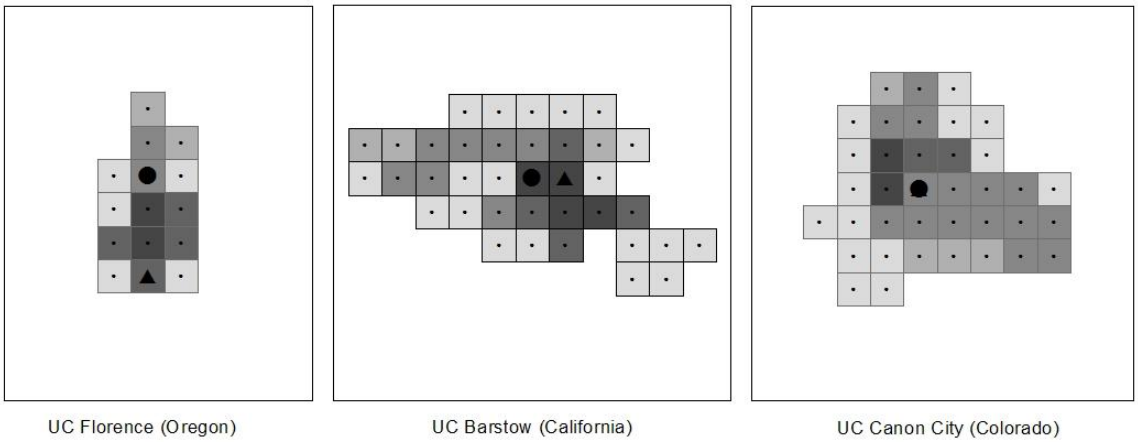
[28]Choosing the size of the cells yields a trade-off between the accuracy and speed of the algorithm. Vicentini (2012) follows a similar approach in his dynamic model, dividing the city of Greensboro into cells of 2.25 square miles (1.5x1.5).

FIGURE 2.4.4

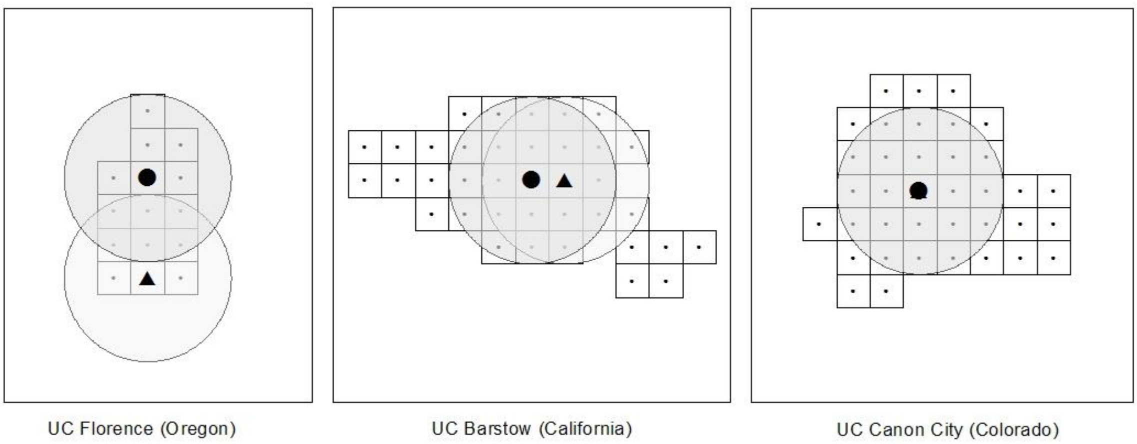
DATA VISUALIZATION FOR SOME SAMPLE MARKETS.



(a) Discretized locations



(b) Population distribution



(c) Trade areas

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 2.4.4(a) visualizes the discretized structure for three example markets, and Figure 2.4.4(b) 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 2.4.4(c) 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 2.4.1 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 distribution 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

TABLE 2.4.1

DESCRIPTIVE STATISTICS OF OBSERVED LOCATION CHOICE.

Variables	observed outcomes							
	Kroger				Safeway			
	mean	st.dev.	min	max	mean	st.dev.	min	max
exogenous variables:								
$\bar{X}$	15.0625	(10.7861)	0.8196	44.3463	15.2931	(11.2544)	0.8196	44.3463
Z	1.1495	(0.7075)	0.2841	3.2698	1.1615	(0.6229)	0.2556	2.8767
BB_distance	0.0644	(0.1188)	0.0012	0.4672	0.0597	(0.1121)	0.0017	0.4242
av_Age	39.4228	(6.7055)	25.0114	54.4940	39.4624	(6.7941)	25.0114	54.5760
av_HHsize	2.3810	(0.2217)	1.9098	2.8331	2.3672	(0.2111)	1.9844	2.7899
endogenous variables:								
$Captive/\bar{X}$	0.1280	(0.2613)	0	1	0.1392	(0.2474)	0	1
$\Delta Captive/\bar{X}$	-0.0756	(0.3196)	-1.5661	0.3780	0.0177	(0.2132)	-0.6078	0.6103
$\rho_{captive}$	0.1791							
$(p - value)$	(0.3349)							

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 2.4.1, the population of a trade area is never zero and so the endogenous variables will always be defined.

2.5 Estimation results

Estimating the model as outlined in Section 2.3, Table 2.5.2 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. Models (3) and (4)

TABLE 2.5.2
ESTIMATION RESULTS.

	without rivals		with Big Box rivals	
Variables	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.

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 2.F.4).

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 justified 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.[29] 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 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

[29] Allowing 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.

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.

2.6 Discussion

2.6.1 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.

2.6.2 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,

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

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 2.4.4(b), 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 be 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.

2.6.3 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.

2.7 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.

2.A Appendix: Toy model

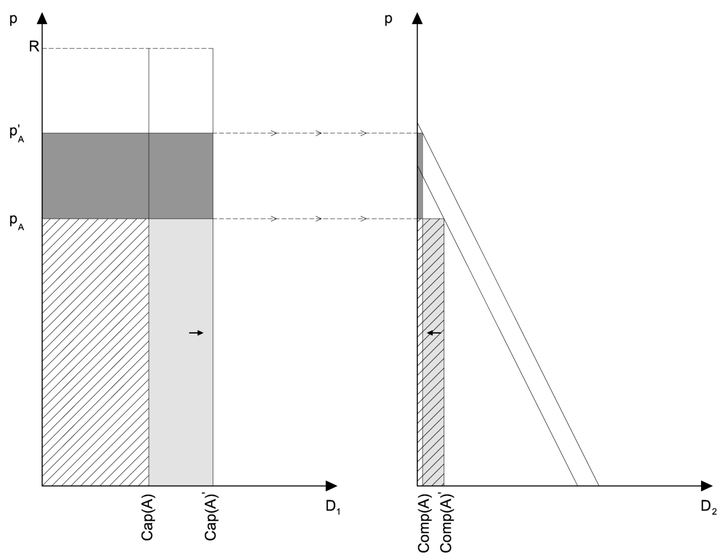
Here, I provide some exercises and the main insights derived from using the Hotelling framework as a simplified market setting as illustrated in Figure 2.2.1. This exercise is especially relevant for the theoretical understanding of the firms' strategy, and will be useful for the interpretation of the empirical results.

Normalizing the competitive area to one, i.e., $\bar{AB} - 2a \equiv 1$, 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 $Max \left\{ p_a(\hat{X}_A + \hat{a} + \frac{1}{2} - \frac{p_a - p_b}{2t}) \right\}$, 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 2.A.1 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 $R(X_A + a) \geq p_a^*(\frac{X_A+a}{\bar{X}_A} + \frac{\tilde{x}^*}{\bar{X}_A})$ with $p_a^* = \frac{4}{3}t\frac{X_A+a}{\bar{X}_A} + \frac{2}{3}t\frac{X_B+a}{\bar{X}_A} + t(1 - \frac{X_A+a}{\bar{X}_A})$ and $\tilde{x}^* = \frac{(1-\frac{X_A+a}{\bar{X}_A})}{2} - \frac{1}{3}(\frac{X_A+a}{\bar{X}_A} - \frac{X_B+a}{\bar{X}_A})$. 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 2.A.1

THE EFFECT OF AN INCREASE IN CAPTIVE CONSUMERS.



2.B Appendix: Detailed calculations of variables

2.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,

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

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

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., $\phi_{l'}^{-F} \equiv P(covered_{-Fl'} = 1|\mathcal{I}_m^F) = \sum_k A_{kl'} \cdot BP_k^{-F}$, 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 $E_{BP^{-F}}[Captive_{-Fl}] = \sum_{l'}(1 - A(l, l')) \cdot \phi_{l'}^{-F} \cdot X_{l'}$. Hence, the expected difference between captive consumers is given by $Captive^e_{Fl} - Captive^e_{-Fl}$, which yields equation (B.2).

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,

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

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

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 2.B.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:

$$\begin{aligned}
E[Captive_F|s(F)l] &= f^e_{s(F)l}(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) \\
&= \sum_{l'} \left[[\phi_{l'}^{F,N_F-1}(1 - A(l,l')) + A(l,l')] \cdot (1 - \phi_{l'}^{-F,N_{-F}}) \right] \cdot X_{l'} \\
E[Captive_{-F}|s(F)l] &= f^e_{s(-F)l}(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) \\
&= \sum_{l'} \left[[(1 - \phi_{l'}^{F,N_F-1})(1 - A(l,l'))] \cdot \phi_{l'}^{-F,N_{-F}} \right] \cdot X_{l'} \\
E[\Delta Captive_F|s(F)l] &= g^e_{s(F)l}(d_{s(F)}, BP^{s(F)}, BP^{s(-F)}, A, X) = f(\cdot) - g(\cdot) \\
&= \sum_{l'} \left[[\phi_{l'}^{F,N_F-1}(1 - A(l,l')) + A(l,l')] - \phi_{l'}^{-F,N_{-F}} \right] \cdot X_{l'}
\end{aligned}$$

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.

$$
\begin{aligned}
E[Captive_F] &= E[f(d_F, d_{-F}, A, X)] \\
&= E[\sum_l captive_{Fl} \cdot X_l] = \sum_l E[captive_{Fl}] \cdot X_l \\
&= \sum_l E[I\{\sum_{k=1}^{L} d_{Fk}A_{kl} > 0\} \cdot (1 - I\{\sum_{s=1}^{L} d_{-Fs}A_{sl} > 0\})|s(-F)] \cdot X_l \\
&= \sum_l P(captive_{Fl} = 1) \cdot X_l \\
&= \sum_l P(Ncovered_{Fl} \geq 1 \cap Ncovered_{-Fl} = 0) \cdot X_l \\
&\quad \text{by Conditional Independence Assumption:} \\
&= \sum_l P(Ncovered_{Fl} \geq 1) \cdot [1 - P(Ncovered_{-Fl} \geq 1)] \cdot X_l
\end{aligned}
$$

$$
\begin{aligned}
&\text{(1.) for } N_F = 1: \\
P(covered_{s(F)l} = 1) &= E[I\{\sum_{k=1}^{L} d_{s(F)k}A_{kl} > 0\}] \\
&= P(d_{s(F)1}A_{1l} = 1 \cup d_{s(F)2}A_{2l} = 1 \cup ... \cup d_{s(F)l}A_{Ll} = 1) \\
&\quad \text{by Mutually Exclusive Choices:} \\
&= \sum_k P(d_{s(F)k}A_{kl} = 1) \\
&= \sum_k A_{kl} \cdot P(d_{s(F)k} = 1) \\
&= \sum_k A_{kl} \cdot EP_k^{s(F)} \equiv \phi_l^s(BP^{s(F)}) \quad \text{result how firms form their expectations}
\end{aligned}
$$

$$
\begin{aligned}
&\text{(2.) for } N_F \geq 1: \\
P(Ncovered_{Fl} \geq 1) &= E[I\{\sum_{s(F)} \sum_{k=1}^{L} d_{s(F)k}A_{kl} > 0\}] \\
&= E[1 - I\{\sum_{s(F)} \sum_{k=1}^{L} d_{s(F)k}A_{kl} = 0\}] \\
&\quad \text{since} \quad covered_{s(F)l} \sim Bernoulli(\phi_l^s) \\
&\quad \Rightarrow Ncovered_{Fl} \sim Binomial(N_F, \phi_l^s)
\end{aligned}
$$

2.C Appendix: Considered Markets

Table 2.C.1

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	(15624)	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	49571
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 2.C.2

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	43.50	153.12
	(13.89)	(53.37)	(346.50)
population density (pop/mi^2)	1654.77	2029.84	2354.61
	(673.72)	(846.10)	(1124.96)
households	8430.35	40333.69	198349.41
	(5936.29)	(70777.15)	(542684.26)
locations (1×1 mile cells)	33.71	79.07	222.35
	(20.79)	(72.90)	(438.48)
number of Kroger-stores	1	2.27	8.97
	(0)	(4.76)	(25.50)
number of Safeway-stores	1	2.66	9
	(0)	(2.99)	(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 donâĂŹt 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 âĂŸnoiseâĂŹ 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.).

2.D Appendix: Knitro problem specification and outcome

As specified in Section 2.3, I formalize the equilibrium conditions of the game as non-linear 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, including the individual iteration steps and the final statistics.

Figure 2.D.2
Knitro outcome (baseline model).

```
   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

===============================================================================
```

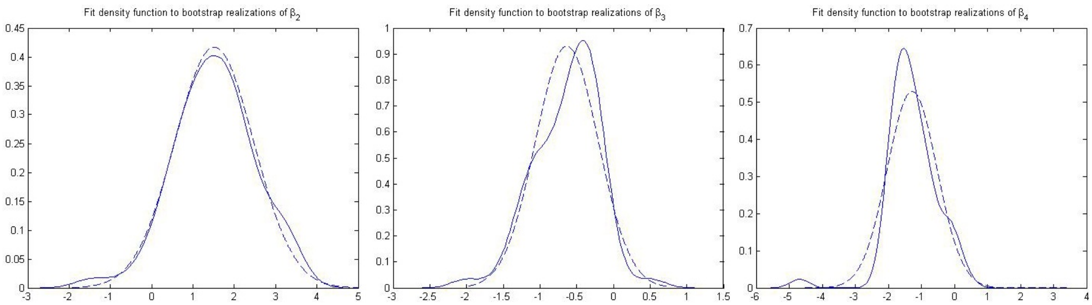
Notation: iteration number (Iter), cumulative number of function evaluations (fCount), value of the negative log-likelihood function (Objective), feasibility violation and the violation of the Karush-Kuhn-Tucker first-order condition of the respective iteratations (FeasError,OptError), distance between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

2.E Appendix: 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.

Figure 2.E.3

Bootstrap distribution (baseline model).



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. Table 2.E.3 indicates the quantiles of interest and the probability of a negative coefficient for the model specifications (1)-(4).

TABLE 2.E.3
BOOTSTRAP DISTRIBUTION

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

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

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

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

2.F Appendix: 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. Allowing

Table 2.F.4
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

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.

CHAPTER 3

A new supermarket in the neighborhood: The price reaction of incumbent retailers

3.1 Introduction

Models of oligopolistic price competition in general suggest that an increase in the number of firms in the market decreases prices. However, little is known about the dynamics of price reactions when a new supermarket opens its doors. In this paper, I aim to analyze empirically whether market entry induces incumbent firms to adjust prices instantaneously, step-wise or with a delay. I analyze this question using the price indexes of a standard shopping basket and expect new insights into the general repositioning of stores. Currently, we observe in the British market that Tesco has decreased prices for several products of a standard shopping basket as a reaction to the competitive pressure of the new German retailers Aldi and Lidl. But can we generalize this observation for other markets and any type of new supermarket? Considering data for urban supermarkets in the City of Madrid, descriptive statistics show for stores that face entry into their neighborhood a significant price decrease with respect to supermarkets without entry in their trade area. But how quickly do incumbents react to new players? This paper analyses the competition effect on supermarket prices, differentiating the effect of incumbent stores and new entrants. This distinction allows us to distinguish between long-run competition effects and immediate competition effects when a new supermarket opens its doors.

To analyze this question, I use a new dataset of quarterly normalized price indexes for supermarket stores in the city of Madrid (Spain). To be precise, I use different types of data to build a panel dataset of relative price indexes at the store level and associated store location-specific characteristics. In particular, I use a quarterly price survey for a sample of supermarkets in Madrid containing the street address of each store and normalized price indexes of a standard shopping basket. Additionally, I use census data to identify all the supermarkets in the urban area and the distribution of economic and demographic characteristics within the city. Using the geographic information system ArcGIS, I construct a unique panel dataset with quarterly data from 2009-2011. While in a parallel work Asensio (2013) uses only one time period of this supermarket data to emphasize the price-flexing practice of Spanish supermarket chains, the present paper focuses on the dynamics of the price of a standard food basket, in particular the price reaction over time to a new store opening and the effect on the relative position of a store with respect to competitors.

The literature explaining the variation in supermarket prices can be classified in terms of price variations due to changes in the wholesale price or cost changes, on the one hand, and changes in the retail margins on the other hand. The latter can be differentiated into two approaches: behavior-based inter-temporal price discrimination ('sales approach') and competition-referenced pricing ('competitive outcome').

Considering the price evolution of a particular product, abstracting from competition, several papers have identified sales cycles in supermarket pricing. Examples are Hosken and Reiffen (2004), who analyze the price variation of different supermarket products using monthly prices at the store level for different cities and find that there is typically a 'regular price', with most of the deviations identified as temporal sales. Explanations for this kind of observed temporal sale are proposed by Ariga et al. (2010) as an incentive of the supermarket to discriminate between consumers who buy for immediate consumption and those who buy for inventory, and by Dubé at al. (2008) as a result of the firm's incentive to achieve consumer loyalty. However, since promotions are in general product-specific and last from a few days to one month, these arguments cannot be used to explain the observed variation in the price index of a standard shopping basket. On the one hand, Kopalle et al. (2009) argue that in a fixed-weight price index the demand effect of the sales is not captured. On the other hand, it seems reasonable to assume that product-specific sales do not last more than one month and so they may not be considered when using quarterly evaluation.

Studying price changes as an outcome of imperfect competition, many of the existing empirical papers are cross-sectional, and focus implicitly on the long-run competition effect in a particular industry and market (Singh and Zhu (2008), Gullstrand and Jörgensen (2012), Asensio (2013)).

This paper in turn considers dynamics in the competition effects, differentiating between the immediate competition effect of a new entrant and the long-run competition effect of changes in the market structure.[30] Throughout the paper, I will use the terms 'incumbents' for firms that are established in the market at a certain point in time and 'new entrants' for firms entering the market in the respective period. It is important to notice that according to this definition, in the period after market entry has taken place, the old entrants are now established firms in the market and hence become incumbent firms. One of the closest analyses to my own is that of Basker (2005, 2009), who analyzes empirically the effect of Wal-Mart's entry on the pricing of incumbent retailers. Using quarterly city-level prices for different products, he finds significant price decreases that are stronger in the long run than in the short run, larger in cities with less incumbent firms per capita, and smaller for the big three players than for other retailers. For the analysis, I set up a reduced-pricing equation that differentiates competition effects in the competition effect of incumbent stores and the entry effect of a new grocery retailer. Given that entry into the Spanish supermarket industry is strongly regulated, in the sense that firms have to apply for licences a long time in advance to entry, which produces a time lag between the entry decision and the realized entry, we argue that a potential simultaneity problem of entry and pricing is not an issue but that the required approval by the regional regulation authority induces a potential selection bias in the estimation. Under the assumption of selection on time-constant market characteristics, we make use of the panel data and propose a first-difference approach.

The results suggest the immediate price adaptation of Spanish supermarkets upon the entry of a new supermarket store, which is lower than the competition effect of

[30] For a general discussion of the literature and further challenges analyzing the interaction between pricing and competition effects see, for example, Kopalle et al. (2009).

incumbent firms. To be precise, I find that, on average, the entry of a new supermarket in the neighborhood leads to an instantaneous price decrease by established stores of 1.26%, and the full (long-run) competition effect implies an average total price decrease of 2.11%. This implies a differentiation in short-run and long-run competition effects which may be explained by the constrained price flexibility of Spanish supermarkets in the short run, or that new stores need time to establish their business as a fully-fledged rival in the local market. Moreover, we find that the difference between the entry effect and the competition effect of incumbent firms is especially pronounced for supermarkets positioned in the middle price-segment, and that, high-price stores react the strongest to changes in the market structure.

The article proceeds as follows. First, I introduce the industry and the dataset with a special focus on how to deal with normalized price indexes. After providing some descriptive statistics that motivate the analysis, I provide an econometric approach and the results. Finally, I comment on pending work and future research.

3.2 The grocery retail industry in Spain

With a contribution of 7-8% to overall GDP, the food sector is one of the most important industry sectors in Spain. However, it is also a very dynamic sector, where changes in technological innovations and consumer behavior bring along challenges for traditional retailers such that administrative measures have been taken to protect small-scale firms.

A key feature of the supermarket industry in Spain is that the sector is highly regulated and that the regulation is decentralized. While there exist general guidelines at the national level, the autonomous regions have a large degree of leeway to decide the terms of opening hours and the dates of sales periods and entry conditions for certain formats of commercial establishments, while some decisions, for example Sunday or Holiday shopping days, are delegated to the municipalities. A good summary of the evolution of the legislative regulations at the national level and that of the autonomous regions can be found in Matea and Mora (2012). For my analysis, focusing on the city of Madrid and regulation at the national level, the autonomous region level and the municipality level are the same for all considered supermarket stores, so that there is no variation in the legal framework which may alter regional prices. Concentrating on the implementation of regulations in the Community of Madrid, the Competition Court of the Community of Madrid has the main task of guaranteeing effective competition in line with the legislation of the Community of Madrid. This legal framework includes information about the opening of large-scale retail formats and discounters, although medium-sized retailers are also subject to approvals. While the Competition Court has a solely informative role, the authorization or modification of certain retail businesses is undertaken by the Regional Ministry of Economy and Finance of the Community of Madrid. In the following, I comment briefly on the types of businesses that are especially strongly regulated and which comprise a large proportion of all the establishments.[31] A large retailer needs a second special licence from the autonomous community in addition to the licence of the corresponding town hall to enter the market at a particular location. For the City of Madrid, this includes all retail establishments of at least 2.500 m^2. Discount retailers are likewise required to apply for a specific licence and this applies to all retailers with a minimum number of white-label products compared to branded products (> 70%), an affiliation with a multi-store company or chain, a minimum sales area (> 500 m^2) and a minimum sales volume (> 3 billion Euros). Last, but not least, since 2001 medium-sized retailers with a floor space of at least 750 m^2 are also subject to the approval of a specific licence from the Regional Ministry of Economy and Finance. In 2012, the law 'Dynamization of the Commercial Activity in Madrid' relaxed the strong administrative and urban requirements for retail establishments although, given our data from 2009-2011, this period is out of sample.[32]

Considering the market structure, the supermarket industry in the City of Madrid is dominated by several large supermarket chains which are associated with a certain format, service and product quality. Table 3.2.1 provides an overview of the active stores in 2010.

[31] Ley 16/1999, de 29 de abril, de comercio interior de la Comunidad de Madrid, Capítulo II, §17., Capítulo III, §24.; Ley 14/2001, de 26 de diciembre, de Medidas Fiscales y Administrativas, §17.

[32] Ley 2/2012, de 12 de junio, de DinamizaciÃşn de la Actividad Comercial en la Comunidad de Madrid.

Table 3.2.1
The grocery retail industry in the City of Madrid

Main Retail Groups[1]	Banners (number of stores, Alimarket census 2010)
Ahorramás (Spain) [2]	AhorraMas (82)
Auchan (France)	Alcampo (4), Aro Rojo (3),
	Simply City (10), Simply Market (5)
Carrefour (France)	Carrefour (5), Carrefour City (9),
	Carrefour Express (9), Carrefour Market (2)
Condis (Spain) [2]	Condis (25)
Dia (Spain)	Dia (110), Maxi Dia (11), Dia Market (88)
Dinosol (Spain)	Supersol (21), Cash Diplo (1)
El Corte Inglés (Spain)	Supermercado El Corte Inglés (7), Supercor (6),
	Opencor (28), Hipercor (4), Convenience Store (1)
Eroski (Spain)	Eroski (2), Eroski City (18), Eroski Center (14),
	Caprabo con Eroski (40)
Híper Usera (Spain) [2]	Híper Usera (16), Híper Aluche (1)
	Híper Villaverde (2), Cash IFA - Híper Usera (3)
Lidl (Germany)	Lidl (29)
Roig (Spain)	Mercadona (31)
Unide (Spain) [2]	Gama (18), Udaco (35), Maxcoop (17)

[1] Retail groups operating at least 20 stores in the City of Madrid. The non-listed stores belong to retail groups with a significantly smaller presence in this urban market (Aldi, C.C. Darbe, Covirán, Eco Mora, Ferjama, Franco-Mor, Miquel, Supermercado Sánchez Romero, Villa de Madrid) or else belong to small firms. [2] Integrated in the IFA Retail group.

As a pioneer project in Europe, the government decided to provide consumers with more transparency and information about prices across supermarkets and initiated the 'Observatorio de precios', a quarterly study of price indexes at the store level that was published on the Web. However, in 2011 the firms complained that the prices did not reflect the product quality and services provided, which could be misleading for consumers, and the government finally stopped this initiative and removed the comparison from the Web. However, some firms continued sharing partially their own monitoring of their rivals' prices with consumers, as an advertisement strategy.

3.3 The data

(1) Price indexes at the store level

The main data for my analysis come from the aforementioned survey of the Spanish Ministry of Industry, Tourism and Commerce, which collected from 2008-2011 quarterly food price data for the main national and regional grocery chains in Spain. The data are provided as price indexes at the store level. In each period, the sample covers more than 4,000 stores in the 56 mayoral cities in Spain, whereby the stores are identified by their exact street address, format and chain affiliation. For each store, 187 products were tracked to construct individual price indexes for the stores which were then normalized within a city with respect to the cheapest basket. That is, considering a particular city, for a store i at period t, the normalized food price indexes can be expressed as follows,

$$FPI_{it} \equiv \frac{P_{it}}{min_j\{P_{jt}\}} \cdot 100$$

with P_{it} being a fixed-weight price index of a standard shopping basket.

The analysis in this paper is restricted to the panel data for the City of Madrid, whereby in each quarter between 209 and 212 hypermarkets, supermarkets and discount retailers are observed, of which 181 stores were continuously tracked through all the periods. [33] Preparing the data for the analysis, I construct a panel dataset of price indexes at the store level. I assign an identification number to each store that has been tracked by the survey at some moment between the first quarter of 2009 and the second quarter of 2011. Each store is identified by the exact street address and the banner. Subsequently, the quarterly data are merged to a panel dataset. Finally, in order to analyze the data in its geographic context, I convert the street addresses of the observed stores to longitude and latitude coordinates using the geocoder of Google Maps.[34] Next, the geographic information system ArcGIS is used to map the geographic data and project them in an x-y coordinate system to be analyzed.[35]

[33]Since the prices in each city have been normalized with respect to the cheapest store within the urban area we cannot exploit cross-city variations, but we may consider other urban areas for a sensitivity analysis of the results.

[34]With the aim of achieving a highly accurate match, when the house number was missing but the store belonged to a mall, I geocoded the mall site. Otherwise, I verified the exact position on the street using Google's street view.

[35]For the projection I use the cylindrical Universe Transverse Mercator (UTM) projection for the area of Spain, which corresponds to the UTM Zone 30.

(2) Census data

In order to identify changes in the market structure, I use the census data from the publisher Alimarket, which provides the exact street addresses of all grocery establishments within the City of Madrid (supermarkets, hypermarkets and discounters) and the associated opening dates.[36] The census data contain the exact opening date of each store which is used to identify the entry decisions. The data do not directly provide the closing dates, but I infer the timing of the market-exit decision of a store from a comparison of the census data of different years. In order to merge the census data from 2008-2011 and to guarantee the consistency of the data, I match the data by the street address and the banner. The apparent independence of the data collection of different years requires a correction of different spellings of the street addresses. A few observations appear in the census only after the year of entry, so that I correct for this inconsistency taking the opening date as the true reference. Additionally, I account for 'banner changes' within a chain and transformations within a retail group which may be falsely considered as market entry but which do not constitute true entry decisions (which can in general be verified given the opening date). Since I am interested in the analysis of the urban grocery market, I exclude one store location from the data which is situated inside the 'Pardo' distrit, a forested area with only a tiny urban area next to the royal palace. Based on the merged census data, I identify all the stores for which prices have been tracked and assign the corresponding identification number.

(3) Demographic and economic data

Additional to the store datasets, I use information on the distribution of demographic and economic data within the considered market using data from the Statistic Institute of Madrid for the smallest available administrative unit. In particular, I use quarterly population data for each neighborhood district (128 'barrios') and housing prices at the superordinate district level (21 'distritos'). The Community of Madrid also provides shapefiles of territorial borders for districts and neighborhood units which I use for the spatial association of these variables.

[36] Since the freely available information is limited, I am grateful to Javier Asensio who provided, in collaboration with the University of Valencia, the complete census data of Alimarket for the years 2008-2011.

3.4 Descriptive statistics

Table 3.4.2 indicates the changes in the market structure for the considered time periods.

TABLE 3.4.2

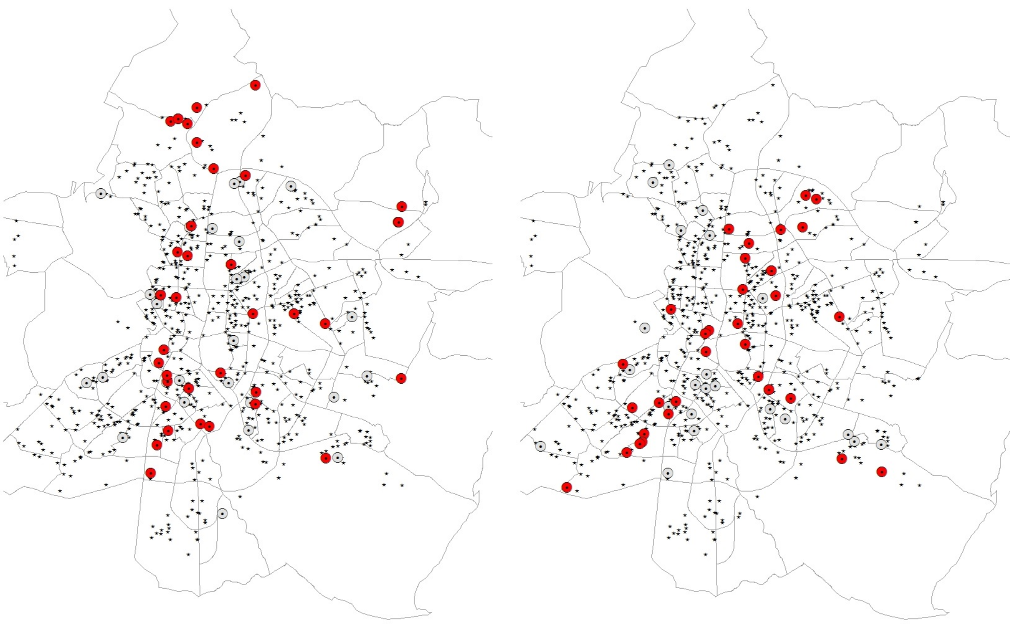
MARKET ENTRY WITHIN THE CONSIDERED TIME PERIOD.

	2009				2010				2011	
	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
Entry	7	11	9	9	4	7	11	10	3	5
Total number of stores	730	741	750	759	738	745	756	766	742	747

The observed entry events are accomodated, approved entry. The second row indicates the total number of stores within the market. Since we can only infer a market exit from the comparison of annual census data, we correct at the beginning of each year for the stores which exit the market in that year. That is, we make the strong assumption that firms that exit the market are not profitable and that this is anticipated by all firms at the beginning of each year. Complementary to this, Figure 3.4.1 illustrates the geographic distribution of all the grocery stores in the City of Madrid

FIGURE 3.4.1

CHANGES IN THE MARKET STRUCTURE.



(a) Market entry and exit 2009.

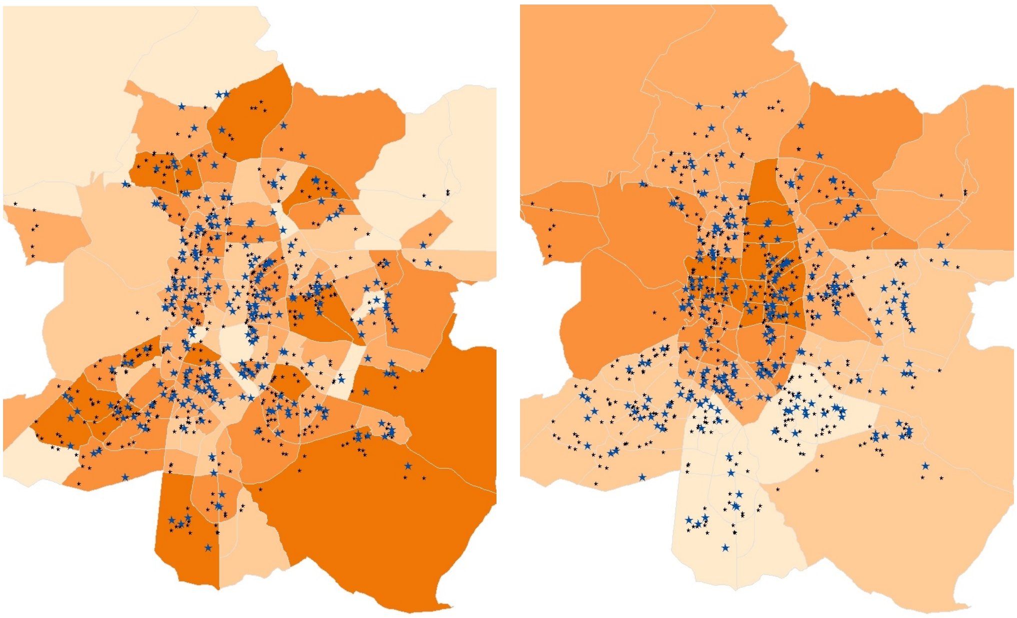
(b) Market entry and exit in 2010.

and the market entry events for the years 2009 and 2011. Since the price survey has been realized for a random sample of all the stores, Figure 3.4.2 illustrates (with blue stars) those stores that have been tracked by the survey. Additionally, the figures present (with black stars) all the incumbent retail stores as well as the population distribution at the neighborhood level and the distribution of housing prices at the district level for the first quarter in 2009, with a darker shaded area being associated with a higher population density and higher house prices, respectively.

A preliminary check of the spatial distribution of the observed store locations and

FIGURE 3.4.2

TRACKED GROCERY STORES.



(a) Population distribution (b) House prices.

the corresponding prices suggests that most of the tracked stores are located in very densely populated urban neighborhoods of Madrid. Complementary to the graphical illustration, Table 3.4.3 provides some summary statistics of store-location variables for the whole period of analysis, from the first quarter of 2009 to the second quarter of 2011.

TABLE 3.4.3
SUMMARY STATISTICS.

	Mean	Sd.dev.	Min	Max
sales area of the store (in m^2)	1262.95	(2307.73)	50	13000
incumbent stores	19.19	(9.62)	1	41
population within the trade area (in 100)	671.02	(270.07)	36.73	1222.62
house price at the store location (in €/m^2)	3659.86	(907.62)	2041	5406

Considering the normalized prices across stores reveals the price flexing policy of Spanish supermarkets, i.e. the supermarket chains set different prices for their stores within the same geographic market. However, the paper focuses on the price variation which requires, first of all, the redefining of the price data. Recall that the price indexes are normalized in each period with respect to the cheapest store in their respective periods that can differ over time. Hence, to make the data comparable over time, I define a reference store r, that will be the same throughout the analysis, and consider the evolution of the prices of each store with respect to the reference store. That is, we change the normalization such that the price ratio, which we use for the analysis, is calculated as follows:

$$p_{it} = \frac{FPI_{it}}{FPI_{rt}} = \frac{P_{it}/min_j\{P_{jt}\})}{P_{rt}/min_j\{P_{jt}\})} = \frac{P_{it}}{P_{rt}}$$

As an interesting fact, comparing the average volatility of the prices (within variation) and the average price flexing among the stores (between variation) for each chain, the data show a significant correlation between the volatility and the price flexing practice. This suggests that those firms practising a high degree of price flexing are also likely to employ considerable price changes over time.

Table 3.4.4 reports the average price changes of stores that face a new entrant in period t within a radius of 1 km and those stores that are further away from the new establishment.

TABLE 3.4.4
PRICE CHANGES ASSOCIATED WITH MARKET ENTRY IN PERIOD T

price lags	average price change		$H_0 : \mu_1 \neq \mu_2$
	$(entry \leq 1km)$	$(entry > 1km)$	p-value
$p_t - p_{t-1}$	-1.37 % (3.70)	-0.41 % (3.54)	0.0001
$p_{t+1} - p_t$	-1.11 % (3.31)	-0.45 % (3.67)	0.0090
$p_{t+2} - p_{t-1}$	-0.29% (3.45)	0.16 % (3.23)	0.5934

The first row compares the average price changes with respect to the pre-entry period. The data suggest a significant difference between the price adjustment of the two groups. The supermarkets that face a new entrant in their trade area seem to instantaneously decrease their prices. The second row compares the price changes in the period after entry, and likewise shows a significant decrease for the stores that face new rivals. This may suggest a delayed price adjustment after entry has taken place. However, the last row shows no significant difference between the price adaptation in subsequent periods. We will investigate whether this pattern can indeed be interpreted as a gradual two-period price adjustment due to the market entry of a new supermarket in the neighborhood. [37]

In our data, 73% of all the tracked stores experience entry at some point of time within the considered time horizon. The reference store is chosen at random from the subsample of 11 stores for which we observe prices for the standard shopping basket and which experience neither entry nor exit within at least 1 km distance from the store location during the whole observation period. Since four of the stores belong to the retail chain Ahorramas, I choose one of the Ahorramas stores as my reference for the analysis and use the others for a robustness check of the results.

3.5 Estimation approach

Since we are interested in estimating the causal effect of entry on market prices, let us briefly consider the process behind the observed market entry. Given the market structure and the distribution of local characteristics within the urban market, firms

[37] Since we are interested in an econometric analysis of the price dynamics, we run a panel data unit-root test on the price ratios. The HarrisâĂŞTzavalis unit-root test rejects the unit-root hypothesis so that we can rely on the usual econometric procedures.

decide whether it is profitable to enter the market and, if so, which location to choose in order to maximize their profits. Assuming rational firms, the optimal location is the best response to the behaviour of incumbent firms in terms of prices and locations, as well as the distribution of relevant market characteristics. In turn, the prices of incumbent firms are the optimal response to the market entry decision, which implies that, in equilibrium, market entry and prices depend upon each other. Hence, setting up an econometric model that explains prices as a function of market entry, we face a simultaneity problem. However, dealing with a regulated market, let us assume a time lag between the entry decision and the entry realization, which comes from the necessary application and approval by the regulation authority. Next, following the assumptions of Basker (2005) that firms cannot accurately forecast prices, entry will affect the price setting in the entry period but not the other way around. In other words, in a regulated market that causes delays between the entry decision and the realization, any endogeneity bias of the entry coefficient due to simultaneity is not an issue. However, the necessary approval of entry by an external party introduces a potential problem of selection bias when evaluating the entry effect. The Ministry of Economy and Finance is assumed to pursue certain objectives when deciding on the approval or rejection of an entry application, such that entry approval is not a random assignment. However, note that if the decision of the ministry depends upon some unobservable market characteristics which are also price determinants, this produces a kind of omitted variable bias in the entry coefficient that we aim to estimate. Under the strong assumption that entry approval is merely based on time-invariant store-location characteristics, we can write observed market entry as follows,

$$E_{it} = f[g(p_{i,t-k}, X^{all}_{i,t-k}, Z^{all}_{i}), Z^{all}_{i}]$$

where $g(\cdot)$ defines the optimal decision of a firm at time $t-k$ with $k \geq 1$ to enter the market in the neighborhood of store i, and $f(\cdot)$ defines the decision made by the regulation authority based on the received application. Z^{all} accounts for observable and unobservable time-invariant characteristics and X^{all} accounts for observable and unobservable location-specific and store-specific differences that vary over time.

Keeping this in mind, let us consider the following reduced-form price equation which has been used in several papers to analyze competition effects,

$$ln(p_{it}) = \alpha_0 + \alpha Z_i + \beta X_{it} + \gamma rivals_{it} + \epsilon_{it}$$

where Z_i are the observable time-invariant characteristics (like the size of the stores and the chain affiliation) and $X_{it} = (W_{it}, rivals_{it})$ are observable store- and location-specific variables, where W_{it} captures location-specific and store-specific differences like the population mass living within a 1 km radius of the stores or the difference in housing prices at the store location, and $rivals_{it}$ indicates the number of rival stores at a certain point in time. [38] In this model, γ is usually the parameter of interest to be estimated that captures the competition effect. Note that this specification implicitly assumes that all stores exercise the same competition effect, independently of whether they are incumbent stores or whether they have just entered the market, and this could be estimated using cross-sectional data.

In this paper, we are interested as to whether there is an entry effect on supermarket prices and, if so, whether the price adaptation takes place instantaneously or gradually, as well as how to identify the long-run competition effect. In order to address these issues in a reduced price regression, I disclose the number of supermarkets in the trade area of a store in incumbents and entrants in the following way,

$$ln(p_{it}) = \alpha_0 + \alpha Z_i + \beta X_{it} + \gamma Incumbents_{it} + \phi(L)Entry_{it} + \epsilon_{it} \quad \text{with} \quad \epsilon_{it} = w_i + u_{it} \tag{3.5.1}$$

where $Incumbents_{it}$ controls for the existing number of established stores within the trade area and $Entry_{it}$ captures the number of entrants in the respective periods. In order to allow for delayed price adaptations, I will also include the lagged values of entry, but for the moment let us focus on this specification.

Given our reasoning about the process behind the observed market entry, note that if $Cov(p_{it}, Z_{it}^{all} \setminus \{Z_i\}) \neq 0$ and $Cov(Entry_{it}, Z_{it}^{all} \setminus \{Z_i\}) \neq 0$, then our parameter of interest ϕ will suffer omitted variable bias. Hence, for the estimation I propose the use of first-differencing, which results in the following first-difference distributed-lag (FDDL) model:

$$\Delta p_{it} = \beta \Delta X_{it} + \pi_0 Entry_{it} + \pi_1 Entry_{i,t-1} + \Delta u_{it} \tag{3.5.2}$$

[38] Similar specifications have been used by Singh and Zhu (2008), Basker (2009) and Asensio (2013). An alternative approach to model price variations, is to base the estimation on the price reaction function of the firm using a spatial autoregressive model. For applications of the latter see for example Pennerstorfer et al. (2012) and Gullstrand and Jörgensen (2012). It depends on the purpose of the analysis which model-type is preferred.

Controlling for the number of incumbent stores and entry, note that the number of incumbent stores of the next period is the number of the current stores plus entry ($N_{it} = N_{i,t-1} + Entry_{i,t-1}$). This implies that, when taking the first-difference of equation (1), the number of incumbent firms vanishes from the regression specification. The competition effects that we estimate under this specification are $\pi_1 = (\gamma - \phi_0)$ and ($\pi_0 = \phi_0$), such that we estimate the competition effect of a new entrant (ϕ_0) directly and recover the effect of incumbent stores (γ). Note that both the number of incumbent stores and any observed and unobserved time-invariant determinants (e.g., product quality, services, location inside a shopping mall, etc.) may also be determinants of the entry approval by the ministry and they vanish, which prevents potential omitted variable bias from time-constant variables.[39]

In this specification, we expect to find a temporary entry effect on the price reaction of the stores, such that the coefficients of the entry variables are expected to decline over time. If this is the case, then we can interpret the coefficients of the FDDL model as $\hat{\pi_0}$, being the "short run effect" of market entry, while the sum over all the lagged coefficients of entry $\sum_{s=0}^{q} \hat{\pi_s}$ is the "long-run effect", which corresponds to the effect of incumbent stores. Table 3.5.5, panel A, columns (1) and (2), present the estimated coefficients of interest of the FDDL model without and with covariates for the full sample, and Table 3.5.6 provides the corresponding competition effects of interest.

The estimates of the entry effect in columns (1) and (2) suggest an instantaneous, significant price decrease in the entry period, which is robust controlling for population and cost effects. In order to verify whether the entry effect is different from the competitive pressure that is exercised by an incumbent store, note that this is equivalent to test the hypothesis $H_0 : \pi_1 = 0$. Panel A suggests that the coefficient of the lagged entry variable in the FDDL model is significantly different from zero, which implies that the competition effect of a new entrant is different to the effect of an incumbent store. To be precise, the result suggest that entry leads to an instantaneous price decrease of 1.2%, but implies a total price decrease of 2.2%. This can be either interpreted as constrained price flexibility in the short run, or we can argue that supermarkets entering an urban market need one period to position their store as a fully-fledged ri-

[39] Recall that we analyze the effect of accomodated, approved market entry. Note that we do not observe when entry is blocked, deterred or denied by the regulation authority. In this paper I discuss potential endogeneity of entry but do not explain entry behavior but the reaction of incumbent stores to a new store opening.

TABLE 3.5.5

FDDL REGRESSION ON THE PRICE OF A STANDARD FOOD BASKET.

Panel A		Full sample			
		(1), None	(2), ΔX	(3), None	(4), ΔX
π_0	$entry_t$	-.011942***	-.0121336***	-.0073437***	-.0088779***
		(.0023682)	(.0024289)	(.0022614)	(.0022774)
π_1	$entry_{t-1}$	-.0084087***	-.0093975***		
		(.0020829)	(.0020653)		
$\tilde{\pi}_1$				-.0066492***	-.0067946***
				(.0022304)	(.0022176)
π_2	$entry_{t-2}$			-.0009511	-.0025532
				(.0022762)	(.0022661)
Panel B		Differentiation by price segment.			
		low price segment	middle price segment	high price segment	
		(5),ΔX	(6),ΔX	(7),ΔX	
π_0	$entry_t$	-.0162649*	-.0091188***	-.0311733**	
		(.0085604)	(.0020936)	(.0129666)	
π_1	$entry_{t-1}$	-.0051867	-.0100581***	-.0108938	
		(.0070136)	(.0020736)	(.0089116)	

The price index for a standard shopping basket has been normalized with respect to a reference store r. Hence, for ease of interpretation we define all the covariates as the difference with respect to the reference store. That is, we use $\Delta\tilde{X}_{it} = \Delta(X_{it} - X_{rt})$, and the competition effect of incumbent firms refers to a change in $\widetilde{Incumbents}_{it} = (Incumbents_{it} - Incumbents_r)$, which corresponds to a change in $Incumbents_{it}$ since the reference store does not experience any change in the number of stores during the period of analysis.
Significance level: * 0.1, ** 0.05, *** 0.01. Robust standard errors in brackets.

TABLE 3.5.6

SUMMARY OF ESTIMATED COMPETITION EFFECTS.

	Full sample	low price segment	middle price segment	high price segment
	(a)	(b)	(c)	(d)
incumbent stores ($\hat{\gamma}$)	-.02153112***	-.02145158**	-.01917686***	-.04206712***
	(.00289845)	(.00982516)	(.00273631)	(.01381646)
new entrants ($\hat{\phi}_0$)	-.0121336***	-.0162649*	-.0091188***	-.0311733**
	(.0024289)	(.0085604)	(.0020936)	(.0129666)

val in the market, which may be an alternative explanation for the partial competition effect in the entry period. Considering the price indexes of a standard food basket, it may be the case that firms adjust prices instantaneously for some products but, depending upon the contract with the providers, it may take time to adjust the prices of other goods. In order to get an idea about the magnitude of the competition effects, we find that an increase of one standard deviation in the probability of entry implies a decrease of 4.7% of the standard deviation of the normalized price index. This is a moderate effect, and we interpret this as the supermarket industry in Madrid being quite competitive.

Given the difference in the competition effect of new and incumbent firms, we consider potential delayed-entry effects accounting for lagged entry in the price equation.

This introduces a sequence of potentially relevant lags in the FDDL model. Table 3.5.5, columns (3) and (4) present the results for two lags. Estimating the effect of lagged entry in the differentiated equation, we estimate $\pi_1 = \phi_0$, $\tilde{\pi_1} = (\gamma + \phi_1 - \phi_0)$ and $\pi_2 = -\phi_1$. Considering the entry coefficients, this confirms my expectations of a declining lag effect on the price change. However, testing the hypothesis of delayed-entry reaction implies testing the null hypothesis $H_0 : \pi_2 = 0$, which we cannot reject. Hence, the data suggest that there is an instantaneous price reaction to entry which is not as strong as the full competition effect by the incumbent store. Nonetheless, and already in the next period (three months later), the competition effect of the new entrant has been fully realized and there is no persistent effect on the price adaptation.

Panel B differentiates the analysis by price segments and Table 3.5.6, columns (b)-(d) provide the associated competition effects.

Considering the low price-segment, the competition effects are similar to those estimated for the full sample. The entry effect increases slightly so that short-term and long-term competition effects are no longer statistically significantly different. A possible explanation is that low-cost retailers may be more efficient in the sense of being flexible and fast in reacting to changes in the market structure, thereby minimizing the time gaps of price adaptations.

For the middle price segment, the competition effect of an incumbent store is only a little smaller than for the low-price segment. However, it is interesting that the competition effect of a new entrant is only half as large. This implies that these stores are either less flexible in their pricing policy or else new retailers have some work to do in order to settle down in the market on a par with long-established grocery businesses. It has to be mentioned that the standard food price index for each store has been constructed with comparable products such that we do not measure differences in the composition of private labels and branded products, which may explain these time lags in the price adaptation. Hence, this delayed price adaptation may reveal difference in the flexibility of these firms in some senses, starting from the management to binding contracts with upstream firms. In this paper, I will not be able to explore the reason for this pattern further.

Last, but not least, considering supermarket stores that belong to chains in the high price segment, we find a significant negative competition effect for entrants as well as for incumbent stores that is much stronger than that identified for the full sample. The entry of a new supermarket (of the low or high price segment) leads to a price decrease of 3.1%, and the full effect is even 4.2%. In other words, we find that stores in the high price segment react with a relatively strong price decrease to any rival in their trade area, no matter if they have just entered the market. This stronger price reaction is surprising, since I expected them to be sufficiently differentiated from the rest of the stores, and hence to be less sensitive to market entry by other stores. However, the results may be interpreted as evidence of the high price-cost margin of these firms (opposed to low-price stores which don't have much room to adjust prices downwards) and the competitive threat of other supermarkets. Since almost all the entrant events in the analyzed time period are from the low and middle price segments, it remains open as to whether this holds for entrants of the high price segment.

3.6 Limitations, robustness and further research

So far, we have assumed that the approval for entry by the Ministry is based on time-invariant market characteristics. If we relax this assumption, allowing approval for entry to depend upon observed time-variant variables or any type of observed and unobserved variables, our estimates will still be biased. We are currently working on this issue to verify the consistency of the results.

Second, we are implicitly assuming that all the entry observations have been subject to the same approval process. However, for small grocery retailers in terms of the sales area of the store, entry barriers are relaxed. We will investigate how to account for this differentiation in our model.

In this version of the paper, we restrict the robustness analysis of the results to the analysis with respect to the definition of the variables, that is the chosen reference store. Table 3.6.7 reports the competition estimates for the full sample for different reference stores.

TABLE 3.6.7
COMPETITION ESTIMATES FOR DIFFERENT REFERENCE STORES.

ϕ_0	γ	Reference store
-.0121336***	-.02153112***	Ahorramas,
(.0024289)	(.00289845)	Avda. Daroca 300 (Vicalvaro), 28032 Madrid
-.0135573***	-.02230238***	Ahorramas
(.002395)	(.00286516)	C/Sofia 117, C/V PÂž de Ginebra, 28022 Madrid
-.0125363***	-.018398***	Ahorramas
(.0023915)	(.00295826)	C/Maqueda 117 (Galeria Copasa), 28040 Madrid
-.0123088***	-.02175579***	Ahorramas
(.0024199)	(.00284723)	C/Villajoyosa 96, 28041 Madrid

Note that the competition estimates are very stable with respect to the reference store r that we have chosen in order to make the data comparable over time. On average, the entry of a new supermarket in the neighborhood leads to an instantaneous price decrease by established stores of 1.26%, and the full competition effect implies an average total price decrease of 2.11%. In other words, approximately 60% of the total impact on prices takes place instantaneously in the entry period.

Once I have addressed the concerns above, I plan to consider several extensions of this analysis.

First, we may ask whether the entry of a small store is negligible. Hence, it would be interesting to differentiate the competition effects by the size of the entrant in terms of the sales area, which allows to draw comparisons with the literature on Wal-Mart entry.

Second, since the time horizon of our analysis is from 2009-2011, just after the financial crisis, the financial structure of a firm may effect its entry behavior. Firms that have a good access to credits, may enter the market with a low price and recover possible losses later. However, financially distressed firms don't have this option. Since in the considered time period, stores of Spanish chains as well as stores of International chains enter the market, where the latter are expected to have easier access to credit, it may be interesting to differentiate the entry effect by the financial distress of the firm which is comparable to Chevalier (1995), who provides evidence of price changes due to changes in the financial structure of a firm in terms of leveraged buyouts.

Last, but not least, I plan to analyze whether we can identify additionally the pricing pattern at the chain level. Descriptive statistics cause us to suspect that some retail chains of the same price segment monitor their own position and the positions of their rivals. Since firms have access to the published price indexes in the same way as consumers do, keeping track of their own market position may lead to tacit collusion, and it would be interesting to analyze this hypothesis.

Moreover, we may ask whether the entry of a small store is negligible. Hence, it would be interesting to differentiate the competition effects by the size of the entrant in terms of the sales area.

3.7 Conclusion

The motivation of this paper has been to analyze whether we can explain part of the observed volatility of supermarket price indexes as a result of changes in the market structure. The key idea for the econometric analysis has been to decompose the effect of rival stores into the number of incumbent firms and entrants and to use the panel data to estimate a first difference model with distributed lags. The results suggest that grocery retailers in the City of Madrid react to market entry with a gradual price decrease, which begins with an instantaneous reaction in the period of entry and reaches the long-term competition effect in the next quarter. For retailers of the middle price segment, the results suggest that they delay more than half of the price adaptation to the next quarter.

As noted in the last section, when considering the price volatility at the store level for grocery establishments with an affiliation with a retail chain, we have focused on the neighborhood of a store, although the whole store network within and across markets may explain part of the price variations, which would be interesting to analyze with the data used in this paper.

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