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A Micro-Economic Approach to Geographic Market Definition on Local Retail Markets: Demand Side Considerations

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Abstract This paper formalizes an empirically implementable framework for the definition of local antitrust markets in retail markets. This framework rests on a demand model that captures the trade-off between distance and pecuniary cost across alternative shopping destinations within local markets. The paper develops, and presents estimation results for, an empirical demand model at the store level for groceries in the UK.

JEL L11, L13, L41, L81, C35, C73
Keywords Geographic antitrust market definition; discrete choice

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1 Introduction

The definition of the relevant geographic and product markets is a paramount concern in antitrust investigations; see, for example, the Groceries Market inquiry (2007) carried out by the UK Competition Commission.[1] This paper provides an empirical framework for the delineation of local retail markets. In its conceptual part, it formalizes an algorithm to empirically identify local markets. And it proposes measures of the intensity of competition in such markets. One of the key building blocks of this framework is a micro-level demand model that captures consumers' trade-off between pecuniary and distance costs. In the empirical part of the paper, a micro-level demand model is developed that combines firm level and socio-demographic characteristics to estimate UK consumers' preferences for grocery store choice, allowing for heterogeneous sensitivity with regard to distance and pecuniary costs.

Spatial competition and endogenous market definition on the basis of firm level and socio-demographic data have received increasing attention in the academic empirical industrial organization literature. Mehta (2007) and Zwanziger et al. (2002) investigate the US nursing home industry, while Davis (2006) focusses on movie theaters and Smith (2004) on UK grocery retailing. The common approach to market definition is the so-called hypothetical monopolist test which is routinely, though typically informally, applied in antitrust investigations. It iteratively examines the hypotheses that a hypothetical monopolistic owner of successively expanding sets of retail outlets, ceteris paribus, could profitably impose a small, but significant and non-transitory price increase. This test rests on two essential building blocks: a demand-side model that captures consumers' inclinations to switch between outlets; and a supply-side model that captures the change in the hypothetical monopolist's profit from joint ownership as a function of the contemplated price increase and changes in costs. Section 2 of this paper formalizes this test on the basis of units of observations as they are typically available in competition inquiries. This formalism provides the context for the remainder of the paper which focusses on the demand-side considerations of this framework to geographic market definition.

[1] See http://www.competition-commission.org.uk/inquiries/ref2006/grocery/index.htm for details.

On the demand side, the primary determinants of switching that are of interest, and amenable to empirical investigation, are prices and relative distances between consumers and alternative retail outlets. Studies such as those by some of the aforementioned authors, as well as many antitrust inquiries, examine competition within existing market structures and, typically, use aggregate data that are defined on the level of such pre-defined markets, e.g. market shares and population density measures in lieu of actual household locations and distances to stores. With the increasing abundance of micro-level demand data, there appears to be scope for a refinement of the demand side analysis. Following Smith (2004), this paper utilizes matched micro-level data sets to approach demand side considerations to market definition from a micro-econometric perspective. In contrast to Smith (2004), this analysis utilizes price information. Smith's analysis aggregates consumer choices up to 9 UK regions as markets in which firms are assumed to set homogenous prices across their respective stores, and uses a Bertrand-Nash equilibrium assumption to infer price parameters in consumers' conditional indirect utility. The analysis in this paper proceeds on a disaggregated basis. This approach avoids conditioning the analysis on pre-defined notions of market boundaries, as well as other aggregation issues and potential biases that arise when matching up market level shares and population density measures with consumer level demand models.[2]

The paper is organized as follows. Section 2 provides a formal characterization of the algorithm that is commonly referred to as the hypothetical monopolist test; it also proposes measures for the intensity of competition in local markets[3]. This section is intended as the context for the remainder of the paper. The empirical core of the paper starts with Section 3, describing the micro data underlying the analysis. Section 4 provides an outline of the micro-econometric demand model. Section 5 summarizes the main features of the estimation methodology and addresses various related computational aspects. Section 6 presents and discusses estimation results. And Section 7 provides a brief concluding summary.

[2] A variant of the demand model presented in this paper is published as Appendix 4.2 to the UK Competition Commission's Provisional Findings in the Groceries inquiry (2007). The responsibility for that document lies with the Competition Commission.

[3] Measuring the intensity of competition is often important in assessing whether contemplated or anticipated mergers of retail chains induce a lessening of local competition that is substantial enough to warrant structural remedies, such as store divestments or blocking the merger altogether.

2 A Topology for Local Market Topography

2.1 Demographic Market Definition

Partition geographic space into N areas, indexed by $i \in \mathscr{I} = \{1, \cdots, N\}$. In economic geography, these are sometimes referred to as output areas. Associate with each partition a "representative consumer", also indexed by i. Suppose that for each representative consumer i a demand model is estimated, e.g. of the form considered in the empirical part of this paper. Let s_{ij} denote the share of i's demand satisfied at store j, where j belongs to the set J of all stores. And let J_i denote the set of stores that satisfy i's demand, i.e.

$$J_i = \{j \in J : s_{ij} > 0\}.$$

Let μ_i denote the total demand or expenditure brought to the market(s) by consumer i. This, in a sense, captures the demand side of the market.

From the perspective of firm $j \in J_i$, the amount $s_{ij}\mu_i$ is the total demand or expenditure accruing at store j that is attributable to consumer i. Analogous to the demand side of the market, the supply side, from the perspective of store j, is characterized by the set

$$I_j = \{i \in \mathscr{I} : s_{ij} > 0\},$$

i.e. the set of all representative consumers a share of whose demand is satisfied by store j. The total demand accruing at store j is

$$q_j = \sum_{i \in I_j} s_{ij}\mu_i.$$

Next, the impact of a rise in store j's price, p_j, on demand accruing at store k, $k \neq j$, will be examined. Under conventional monotonicity assumptions on consumer preferences, the own-price effect is a reduction in s_{ij} for all $i \in I_j$, while the cross-price effect is an increase in s_{im} for all $m \in J_i \setminus \{j\}$, where $i \in I_j$, i.e. for $m \in \bigcup_{i \in I_j} J_i \setminus \{j\}$; the latter is the set of all stores at which any of store j's customers also shop. Hence, if $k \notin \bigcup_{i \in I_j} J_i \setminus \{j\}$, then demand at store k is unaffected. If, on the other hand, $k \in \bigcup_{i \in I_j} J_i \setminus \{j\}$, then s_{ik}, and therefore demand $s_{ik}\mu_i$, rises for all $i \in I_j \cap I_k$. Therefore, demand q_k accruing at store k depends on the vector or prices

$$\mathbf{p}_k = [p_j]_{j \in \bigcup_{i \in I_k} J_i}.$$

Henceforth, this will be reflected in the notation $q_k(\mathbf{p}_k)$. This dependence of demand accruing at any store on prices of other stores is, of course, an implication of the underlying demand model for different consumers shopping at that store, but each having different sets of choice alternatives.

The chain of inter-dependences of stores' demands and prices allows to define monopolizable markets. These will be collections of stores whose collective price increase is profitable. Such collections will not partition the set J of all stores, i.e. a given store can belong to several monopolizable markets.

Consider a collection of stores C. Total profits of this collection is

$$\pi(C) = \sum_{j \in C} \left[(p_j - c_j) q_j(\mathbf{p}_j) - F_j \right],$$

where c_j and F_j are store j's marginal and fixed costs, respectively.[4] The change in joint profits due to a joint price change is then

$$\Delta\pi(C) = \sum_{j \in C} q_j(\mathbf{p}_j) + \sum_{j \in C} \left[(p_j - c_j) \sum_{k \in C} \left[1_{\{p_k \in \mathbf{p}_j\}} \frac{\partial}{\partial p_k} q_j(\mathbf{p}_j) \right] \right].$$

For practical purposes, a small, but significant and non-transitory price increase (SSNIP) of 5 or 10 percent is the conventional thought experiment. The stores in C belong to the same antitrust market if the change in joint profits $\Delta\pi(C)$ is positive and $\Delta\pi(C \setminus \{j\})$ is non-positive for all $j \in C$; i.e. substitution of marginal consumers away from stores in $C \setminus \{j\}$, e.g. to store j, renders the SSNIP unprofitable, while substitution to stores outside C is too limited to undermine the profitability of the SSNIP. From an operational point of view, in order to define a local market that a particular store, say k, belongs to, this approach would be applied iteratively, starting with $C = \{k\}$ and expanding C by successively adding nearby stores.

Under symmetry assumptions, cross effects will cancel out, leading to a simplification of the expression for $\Delta\pi(C)$. Define the set of consumers that is captive with respect to C by

$$\mathscr{C}(C) = \{i \in \mathscr{I} : J_i \subseteq C\},$$

[4] Marginal costs are treated as constant for simplicity; this can easily be generalized.

and the set of firm j's consumers that are peripheral to C by

$$\mathscr{P}_j(C) = \{i \in I_j : J_i \setminus C \neq \emptyset\}, \quad j \in C.$$

Customers of store j in the peripheral set are those who have store options outside C, i.e. they are marginal or not captive.[5] Then, the effect of the collective price change on joint profits is

$$\Delta\pi(C) = \sum_{j\in C} q_j(\mathbf{p}_j) + \sum_{j\in C}\left[(p_j - c_j)\sum_{k\in C}\left[\sum_{i\in\mathscr{P}_j(C)} 1_{\{p_k\in\mathbf{p}_i\}}\frac{\partial}{\partial p_k}s_{ij}(\mathbf{p}_i)\mu_i\right]\right],$$

where $\mathbf{p}_i = [p_j]_{j\in J_i}$.[6]

Example: As an illustration, consider the following example, visualized in Figure 1. In this example, there are 9 representative consumers ($C1$-$C9$) and 3 stores ($S1$-$S3$).

The consumers choices are indicated by links to the respective store locations, so that

$$\begin{aligned} J_1 &= J_4 = J_7 = \{2\},\ J_2 = J_3 = \{1\} \\ J_5 &= \{1,2,3\},\ J_6 = \{1,3\},\ J_8 = \{2,3\},\ J_9 = \{3\}. \end{aligned}$$

The areas from which demand accrues at the stores are

$$\begin{aligned} I_1 &= \{2,3,5,6\} \\ I_2 &= \{1,4,5,7,8\} \\ I_3 &= \{5,6,8,9\}. \end{aligned}$$

In this example, the prices relevant to the three stores are

$$\begin{aligned} \mathbf{p}_1 &= [p_j]_{j\in\bigcup_{I_1}J_i} = [p_j]_{j\in\{J_2\cup J_3\cup J_5\cup J_6\}} = [p_1,p_2,p_3]' \\ \mathbf{p}_2 &= [p_j]_{j\in\{J_1\cup J_4\cup J_5\cup J_7\cup J_8\}} = [p_1,p_2,p_3]' \\ \mathbf{p}_3 &= [p_j]_{j\in\{J_5\cup J_6\cup J_8\cup J_9\}} = [p_1,p_2,p_3]'. \end{aligned}$$

[5] Note that $\bigcup_{j\in C}\mathscr{P}_j(C) = \{i \in \bigcup I_j : J_i \setminus C \neq \emptyset\} = \{i \in \bigcup I_j : J_i \setminus C = \emptyset\}^c \subseteq \mathscr{C}(C)^c$.

[6] Note that $\mathbf{p}_j$ is the concatenation of $\mathbf{p}_i$ for all $i \in I_j$.

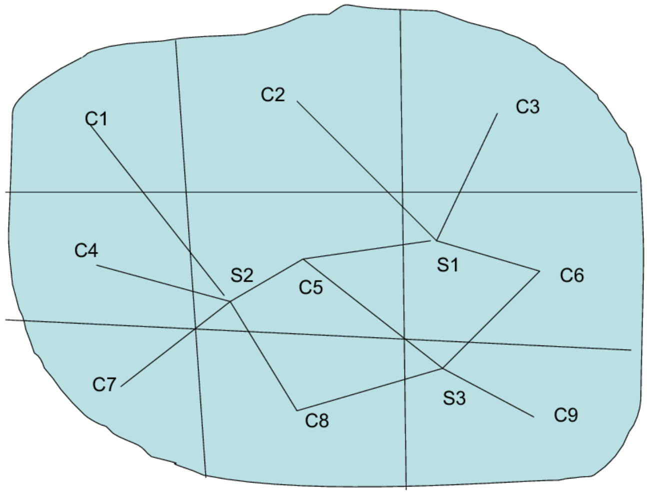

Figure 1: Example of a consumer (C) and store (S) configuration

Consider a coalition of stores $C = \{2,3\}$. For this coalition, since $J_1, J_4, J_7, J_8, J_9 \subseteq C$, the set of captive consumers is

$$\mathscr{C}(C) = \{1,4,7,8,9\},$$

and the consumers peripheral to the coalition members are

$$\mathscr{P}_2(C) = \{5\}, \quad \mathscr{P}_3(C) = \{5,6\}.$$

This completes the illustrative example. □

This setup allows to distinguish different classes of competitor stores of a store k, say, depending on the degree to which these stores are linked to store k via a chain of customers and other stores. This essentially maps out a topography of competition around a given stores or a chain of substitution.

Define the set of direct competitors of store k by

$$C_k^{(0)} = \{j \in J \setminus \{k\} : I_k \cap I_j \neq \emptyset\}.$$

Direct competitors are stores that share customers with store k. The first level of stores indirectly competing with k are those that share customers with direct competitors. Define accordingly the first degree competitive periphery of store k by

$$C_k^{(1)} = \{j \in J \setminus \{k\} : I_j \cap I_m \neq \emptyset, m \in C_k^{(0)}\}.$$

Note that $C_k^{(0)} \subset C_k^{(1)}$. This permits to inductively define the competitive periphery of degree s by

$$C_k^{(s)} = \{j \in J \setminus \{k\} : I_j \cap I_m \neq \emptyset, m \in C_k^{(s-1)}\}, \quad s = 1, \cdots,$$

where $C_k^{(s-1)} \subset C_k^{(s)}$ for positive integers s.

This sequence of sets defines a hierarchy of dependence of store k's strategic decisions, e.g. with regard to price, on the strategic decisions of its competitors. Conditional on the decisions by stores $j \in C_k^{(0)}$, k's decisions are independent of the decisions of store $j \in C_k^{(1)} \setminus C_k^{(0)}$, and therefore independent of the decisions by stores $j \in C_k^{(s)} \setminus C_k^{(0)}$ for $s = 1, \cdots$. More generally, conditional on decisions by stores $j \in C_k^{(t)}$, for some $t = 0, 1, \cdots$, store k's decisions are independent of the decisions of stores $j \in C_k^{(t+1)} \setminus C_k^{(t)}$, and therefore of independent of those by stores $j \in C_k^{(s)} \setminus C_k^{(t)}$ for $s = t+1, \cdots$. This is akin to a backward first-order Markov property operating within the competitive topography around a store.

2.2 Measures of Intensity of Local Competition

Suppose a collection of stores C has been identified as a hypothetically monopolizable market, as above. The set C can be partitioned into non-overlapping sets of stores J_f belonging to different fascias $f \in \mathscr{F}$ out of the set of all fascias $\mathscr{F}$, so that $C = \bigcup_{f \in \mathscr{F}} (J_f \cap C)$.

Denote the hypothetical monopoly profit with respect to the stores in C by

$$\pi^M(C) = \max_{p_j, j \in C} \left\{ \sum_{j \in C} [(p_j - c_j) q_j(\mathbf{p}_j) - F_j] \right\}.$$

Similarly, denote the actual, empirically observable joint oligopoly profits by

$$\pi^E(C) = \sum_{f \in \mathscr{F}} \max_{p_j, j \in (J_f \cap C)} \left\{ (p_j - c_j) q_j(\mathbf{p}_j) - F_j \middle| \mathbf{p}_f^- \right\},$$

where the maximizations are over the set of fascia-level prices, given the optimal level of prices of competing fascias, denoted by $\mathbf{p}_f^- = [p_k]_{k \in C \setminus J_f}$.[7] Finally, denote the hypothetical joint oligopoly profits of stores setting prices individually by

$$\pi^C(C) = \sum_{j \in C} \max_{p_j} \left\{ (p_j - c_j) q_j(\mathbf{p}_j) - F_j \middle| \mathbf{p}_j^- \right\},$$

where $\mathbf{p}_j^- = [p_k]_{k \in C \setminus \{j\}}$. The value $\pi^C(C)$ is the most competitive (hypothetical) profit outcome, given the local market defined by the set of stores C, and can as such serve as a benchmark to assess effective competition. Note that under these hypothetical pricing conduct scenarios, the functional forms of demand accruing at the various stores are assumed to remain the same. This means that it is implicitly assumed that a different store owner/price setter, apart from price, does not alter any other demand relevant features (quality, range, service) of the store. Hence, this approach, as more generally the entire hypothetical monopolist test methodology, amounts to a partial equilibrium analysis.

Since joint profits are expected to be non-increasing with increasing levels of competition, on the basis of these definitions it follows that

$$\pi^M(C) \geq \pi^E(C) \geq \pi^C(C).$$

In other words, the empirically observable profit outcome $\pi^E(C)$ is expected to lie somewhere between two hypothetical extremes, the profit outcomes of the hypothetical monopolistic and the hypothetical competitive conduct. One measure of effective competition one might consider, then, is the ratio

$$s(C) = \frac{\pi^M(C) - \pi^E(C)}{\pi^M(C) - \pi^C(C)} \quad \in [0, 1],$$

which quantifies the degree to which the empirical outcome attains the hypothetical competitive outcome, conditional on the set of stores C.

7 Note that different stores of a given fascia are allowed to charge different prices.

Alternatively, a utility based welfare measure can be considered. Let the hypothetical monopolistic prices be

$$[p_j^M(C)]_{j\in C} = \arg\max_{p_j, j\in C} \left\{ \sum_{j\in C} [(p_j - c_j)q_j(\mathbf{p}_j) - F_j] \right\},$$

and similarly the hypothetical competitive prices

$$p_j^C(C) = \max_{p_j} \left\{ (p_j - c_j)q_j(\mathbf{p}_j) - F_j \middle| \mathbf{p}_j^- \right\} \quad j \in C,$$

while $[p_j^E(C), j \in C]$ denote the observed prices. Then, along the lines of the conditional indirect utility model outlined in the empirical part of the paper, let $V(\mathbf{p}^M(C))$ be the consumers' (aggregate) indirect utility, conditional on the hypothetical monopolistic prices, while $V(\mathbf{p}^C(C))$ and $V(\mathbf{p}^E(C))$ denote the indirect utilities conditional on the hypothetical competitive and empirically observed prices, respectively. With conditional indirect utility, the competitive ranking is

$$V(\mathbf{p}^M(C)) \leq V(\mathbf{p}^E(C)) \leq V(\mathbf{p}^C(C)).$$

Taking the hypothetically competitive outcome as the benchmark, the degree of consumer welfare achieved relative to hypothetical competition can be measured by

$$s^u(C) = \frac{V(\mathbf{p}^E(C))}{V(\mathbf{p}^C(C))}.$$

This completes the formal framework for antitrust market delineation and competitive assessment. It rests on two essential components: the demand model that characterizes switching behavior in response to price changes, such as a SSNIP, conditional on store attributes, such as distance to consumers, amongst others including e.g. range and stores size; and profit calculations, which require cost data or, as a potentially crude approximation, margin data.[8] This framework provides the context for the following demand analysis for grocery shopping in the UK, which explicitly captures consumer heterogeneity in the trade-off between the sensitivity to price and distance.

[8] Davis (2006) carries out an analysis based on margins.

3 Data

The remainder of the paper presents results from the estimation of a micro-level consumer choice model, based on TNS consumer choice data. This analysis is of interest in its own right, as it sheds light on substitution patterns that are relevant in antitrust investigations. The analysis summarized in this part models consumer level choice of supermarket fascia for a consumer's one-stop shopping (OSS) and non-OSS trips.[9]

The TNS data used in this analysis are UK household level data on grocery shopping trips.[10] The sample comprises $n = 11382$ households for whom various socio-demographic measures are observed, such as residential location in terms of UK output area, household size, social grade, ownership of cars and various others which were not used in the present analysis. Each household reports on each grocery shopping trip, using a home scanner, recording date and retail outlet, total spend and an itemized list of grocery items purchased.[11] The present analysis draws on TNS data relating to the 4-week period 09 Oct - 05 Nov 2006 and considers two types of shopping trips: random one-stop shopping (OSS) trips, defined for each household as a random trip out of all shopping trips with expenditure at least 60 percent of average weekly spending; and random non-OSS trips, defined for each household as a random trip out of all shopping trips with expenditure less than 60 percent of average weekly spending.[12].

The TNS data were merged with data on attributes of UK retail outlets by the main retailers, including fascia, location, store size, presence of petrol station,

[9] See below for a definition of OSS and non-OSS. Data on the two types of shopping trips are analyzed separately, although it is recognized that a more comprehensive model of dynamic shopping behavior would account for their dependence through intra-household inventory management.

[10] The TNS data sample was provided by the Institute for Fiscal Studies and the UK Competition Commission.

[11] TNS state that the scanner data are corroborated by purchase receipts which TNS households are asked to submit.

[12] The analysis considers single OSS and non-OSS trips per household. The academic literature to date offers little in terms of tractable dynamic microeconomic consumer choice models, hence this approach, to a considerable extent, is predicated by this fact. A feasible alternative would be to treat multiple trips per household as independent, but as this would presumably be a misrepresentation of the data generating process it was not further pursued in the present analysis

ATMs, cafeteria/restaurant and toilets at the retail outlet.[13] Using mapping software, for each household in the TNS data set a household specific choice set for grocery shopping was constructed which consists of all the stores with net sales area of at least 280 m^2 within 20 mins drive time around the center of the consumer's output area; if there are less than 30 stores for a consumer within 20 mins drive-time, the choice set also includes more distant stores, up to a maximum drive time of 90 mins. As a by-product, household-store distances are recorded as additional store attributes from the household's perspective.[14]

Finally, in order to carry out an analysis beyond a merely hedonic approach which solely rests on non-pecuniary choice attributes, for each store a price measure was constructed. This measure amounts to a weighted average price for a selection of branded goods which are sold by all retailers that are considered in this analysis.[15] Further details on the construction of this price measure are provided in Appendix A.[16]

Summary statistics of the sample of TNS households are given in Table 1, and of the stores in the union of choice sets in Table 2.

[13] The analysis looks at Asda, Coop, Marks & Spencer, Morrisons, Sainsbury's, Somerfield, Tesco and Waitrose.

[14] It is worth noting that not all store characteristics are available for every store. This means that, in the actual analysis, stores for which the respective characteristics are not observed could not be considered. This leads to choice sets for some households which contain fewer than 30 choice alternatives.

[15] Preliminary analyses also experimented with the weighted average price for a wider selection of goods that also includes certain non-branded items, as well as with un-weighted price measures. These measures suffer from potential measurement error due to unobserved quality differences which, in turn, is likely to introduce bias in estimation. They were therefore not considered any further.

[16] There is a concern that the constructed price index does not accurately reflect determinants of consumer choice, especially if consumers are very receptive to discounts. On the basis of the data used for this analysis, it is difficult to identify this kind of shopping behavior, however.

HH size	(in %)	Cars (in %)	Social Grade (in %)		(%)	OSS (Spend, £)	Non-OSS (Spend, £)	Choice (# alt.s)
0	-	15.67	A,B	10.7	5	9.41	1.28	14
1	20.83	51.80	C1,C2	59.0	25	24.63	4.53	19
2	34.93	28.16	D,E	30.3	50	42.52	9.15	23
3	16.76	3.39			75	66.13	16.84	34
4	18.24	0.73			95	111.44	34.72	54
5	6.82	0.15						
≥ 6	2.43	0.10						

Table 1: Broad summary statistics, TNS sample

(%)	Sales Area (net, in m^2)	Distance (in mins)	Price (in £)	Other Attributes (in %)		$\exists \in$ Choice set Fascia	(in %)
min	241	1	2.26	Petrol	31.6	Asda	89.9
25	818	12	2.36	ATMs	70.4	Coop	69.3
50	1640	17	2.62	Café	40.0	M& S	94.6
75	3326	20	3.17	Toilets	58.3	Morrisons	89.3
max	9566	90	4.39			Sainsbury's	92.5
						Somerfield	95.6
						Tesco	98.3
						Waitrose	47.8

Table 2: Store attributes

4 Demand Model

This section describes the empirical model used for analysis. The model follows a wide literature in modern empirical microeconometric demand analysis by allowing for heterogeneity in consumer choice, taking into account differences in consumer characteristics that are likely to shape consumer preferences.[17] The appropriate econometric framework

[17] See, e.g., Hausman and Wise (1978) in the context of discrete response, and Beckert (2005), Dubin and McFadden (1984) and Smith (2004) for joint discrete and continuous choices.

for this analysis is a mixed multinomial logit (MMNL) model for discrete response.[18] The MMNL model is a generalization of the conventional multinomial logit (MNL) model for discrete response[19], overcoming that model's well-known implausibility of independence from irrelevant alternatives (IIA).[20] As a framework for microeconometric analysis of discrete response, this model is also attractive for a number of other reasons. It overcomes some of the computational intractability encountered in other discrete choice models that do not suffer from the IIA property, such as e.g. the multinomial probit model. Moreover, the MMNL model does not rely on severe distributional or functional form restrictions. Indeed, the generality of the MMNL model is due to the fact, first demonstrated by McFadden[21], that, under mild regularity conditions, *any* discrete choice model, arising from a latent random utility model, can be approximated as closely as desired by a MMNL model. The remainder of this section briefly reviews the MNL model and its main properties and subsequently introduces the MMNL model; see McFadden and Train (2000) for further details and discussion.[22]

Denote the indirect utility derived by consumer i from choosing store j in her choice set J_i by

$$u_{ij} = \mathbf{x}_{ij}'\theta + \varepsilon_{ij}$$

where $\mathbf{x}_{ij}$ is a vector of store attributes, possibly interacted with consumer characteristics, θ is a parameter vector, and ε_{ij} is an idiosyncratic utility component that captures unobserved store and consumer taste attributes, for $j \in J_i$. Assuming that ε_{ij} has a type 1 extreme value distribution and is identically and independently distributed across i and j, the model yields MNL choice probabilities

$$P_{ij}(\mathbf{x}_i;\theta) \quad = \quad \Pr(u_{ij} > u_{ik} \ \forall k \neq j; k, j \in J_i)$$

[18] See McFadden and Train (2000) for a comprehensive discussion of the MMNL model, and the literature cited therein. Models of this type have been used previously in the microeconometric analysis of consumer choice in retail markets; e.g. Smith (2004). The MMNL model is an essential building block in most empirical work in industrial organization using market level data, following Berry (1994) and Berry, Levinsohn and Pakes (1995).

[19] See McFadden (1973, 1975, 1984) and Luce (1959, 1977).

[20] See, e.g., Debreu (1960). Nested multinomial logit (NMNL) models (McFadden (1978, 1981)) are an alternative approach to overcoming the IIA problem.

[21] McFadden and Train (2000), Theorem 1.

[22] The MNL model presented here is often referred to as conditional logit because it conditions on choosing within a given choice set, thereby preventing by design any substitution to a potential outside alternative.

$$= \frac{\exp(\mathbf{x}_{ij}'\theta)}{\sum_{k\in J_i}\exp(\mathbf{x}_{ik}'\theta)},$$

where $\mathbf{x}_i = (\mathbf{x}_k')'_{k\in J_i}$.

Let the price of product j, p_j, be an element of $\mathbf{x}_{ij}$, with parameter $\theta_0 < 0$ which is an element of the vector θ. Note that this model, then, yields point own price elasticities of the form

$$\eta_{jj}(\mathbf{x}_i;\theta) := \frac{\partial P_{ij}(\mathbf{x}_i;\theta)}{\partial p_j}\frac{p_j}{P_{ij}(\mathbf{x}_i;\theta)} = (1-P_{ij}(\mathbf{x}_i;\theta))p_j\theta_0,$$

while point cross price elasticities are of the form

$$\eta_{jk}(\mathbf{x}_i;\theta) := \frac{\partial P_{ij}(\mathbf{x}_i;\theta)}{\partial p_k}\frac{p_k}{P_{ik}(\mathbf{x}_i;\theta)} = -P_{ik}(\mathbf{x}_i;\theta)p_k\theta_0, \quad j,k\in J_i,$$

i.e. point cross price elasticities in response to a change in p_k do not vary across j (IIA property), regardless of how close products j and k are located in characteristic space and what relative valuation consumer i places on these.

The MMNL generalizes this model by allowing consumer i's valuation of price and other characteristics to depend on i's observable and unobservable characteristics. In doing so, the model allows for heterogeneity in consumer tastes that permits substitution patterns in response to price changes that capture the consumer's idiosyncratic taste for product attributes. This implies, for example, that the MMNL model allows for consumers who value a certain product attribute, say geographic proximity of a store, to exhibit a higher substitution elasticity with respect to other nearby stores, rather than a substitution elasticity that is uniform across all stores, as in the MNL model.

Define a MMNL model as a MNL model with random coefficients θ drawn from a parametric conditional cumulative distribution function $G(\theta;\mathbf{z}_i,\beta)$, i.e.

$$P_{ij}(\mathbf{x}_i,\mathbf{z}_i;\beta) = \int_\theta P_{ij}(\mathbf{x}_i;\theta)dG(\theta;\mathbf{z}_i,\beta) = \mathbb{E}_\theta\left[P_{ij}(\mathbf{x}_i;\theta)|\mathbf{z}_i;\beta\right],$$

where $\mathbf{z}_i$ is a vector of consumer i's observed characteristics, $\mathbb{E}_\theta[\cdot|\mathbf{z}_i,\beta]$ is the conditional expectation operator with respect to the conditional distribution $G(\theta;\mathbf{z}_i,\beta)$, β is a vector of parameters, and $j\in J_i$.[23]

[23] This notation is more general than maybe needed. Non-random components of θ will have probabilistic point mass at a point and can then be viewed as elements of β.

Notice that the integral is analytically intractable and, hence, must be approximated by simulation. Simulation can be carried out by drawing $\tilde{\theta}_s$, $s = 1, \cdots, S$, randomly from $G(\theta; \mathbf{z}_i, \beta)$, conditional on $\mathbf{z}_i$ and given β, and approximating $P_{ij}(\mathbf{x}_i, \mathbf{z}_i; \beta)$ by its simulated analogue

$$\tilde{P}_{ij,S}(\mathbf{x}_i, \mathbf{z}_i; \beta) = \frac{1}{S} \sum_{s=1}^{S} P_{ij}(\mathbf{x}_i; \tilde{\theta}_s) = E_S \left[P_{ij}(\mathbf{x}_i; \tilde{\theta}_s) | \mathbf{z}_i; \beta \right],$$

where the operator $E_S[\cdot|\mathbf{z}_i; \beta]$ denotes an empirical expectation, or sample average, across the S simulated MNL probabilities $\{P_{ij}(\mathbf{x}_i; \tilde{\theta}_s), s = 1 \cdots, S\}$, evaluated at the simulation sample draws, conditional on $\mathbf{z}_i$ and given β.

As a consequence of mixing, the point own and cross-price elasticities induced by the MMNL model differ from their MNL counterparts, and are given by

$$\begin{aligned} \varepsilon_{jj}(\mathbf{x}_i, \mathbf{z}_i; \beta) &:= \frac{\mathbb{E}_\theta \left[P_{ij}(\mathbf{x}_i; \theta)(1 - P_{ij}(\mathbf{x}_i; \theta))\theta_0 p_j | \mathbf{z}_i; \beta \right]}{\mathbb{E}_\theta \left[P_{ij}(\mathbf{x}_i; \theta) | \mathbf{z}_i; \beta \right]}, \\ \varepsilon_{jk}(\mathbf{x}_i, \mathbf{z}_i; \beta) &:= -\frac{\mathbb{E}_\theta \left[P_{ij}(\mathbf{x}_i; \theta) P_{ik}(\mathbf{x}_i; \theta)\theta_0 p_k | \mathbf{z}_i; \beta \right]}{\mathbb{E}_\theta \left[P_{ij}(\mathbf{x}_i; \theta) | \mathbf{z}_i; \beta \right]}, \quad j, k \in J_i, \end{aligned}$$

so that the point cross-price elasticity is seen to overcome the limitations imposed by the MNL model.

In the particular implementation of the MMNL model considered here, the coefficients on price and drive time distance in the indirect utility are allowed to be random on $\mathbb{R}^2_- = \{\mathbf{w} \in \mathbb{R}^2 : w_1 \leq 0, w_2 \leq 0\}$, with a cumulative distribution function $G(\theta; \mathbf{z}_i, \beta)$ that is jointly log-normal, with a conditional mean that depends linearly on $\mathbf{z}_i$, and allowing for the possibility of correlation between the random coefficients . The vector $\mathbf{z}_i$ is taken to include household size as well as indicators for social groups D and E and of car ownership.

5 Estimation

This section provides a very brief overview of the estimation methodologies appropriate for the empirical models examined in this analysis.

The parameter vector of interest in the MNL model θ can be estimated by maximizing the sample log-likelihood function (ML estimation), obtaining the ML estimator (MLE)

$$\hat{\theta}_n = \arg\max_\theta \left\{ \sum_{i=1}^{n} \sum_{j \in J_i} \delta_{ij} \ln(P_{ij}(\mathbf{x}_i; \theta)) \right\}$$

for a sample of n consumers, where $\delta_{ij} = 1$ if consumer i chooses alternative j, and $\delta_{ij} = 0$ otherwise. Based on the MLE $\hat{\theta}_n$, point own and cross price elasticities can be estimated as $E_n\left[\eta_{jj}(\mathbf{x}_i;\hat{\theta}_n)\right]$ and $E_n\left[\eta_{jk}(\mathbf{x}_i;\hat{\theta}_n)\right]$, respectively, where the operator $E_n[\cdot]$ is defined analogously as above. It is a well known result in classical econometric theory that, if the MNL model accurately captures the true data generating process, i.e. the distributional assumptions underlying the MNL model are valid and the indirect utility function is appropriately specified, then the MLE is consistent, asymptotically normally distributed and fully efficient.

This is to be compared to the estimation methodology suitable for the MMNL. The parameters of interest of the MMNL model, β, can be estimated by maximizing the simulated log-likleihood function (maximum simulated likelihood (MSL) estimation), obtaining the MSL estimator (MSLE)

$$\hat{\beta}_{n,S} = \arg\max_{\beta}\left\{\sum_{i=1}^{n}\sum_{j\in J_i}\delta_{ij}\ln\left(\tilde{P}_{ij,S}(\mathbf{x}_i,\mathbf{z}_i;\beta)\right)\right\}.$$

Simulation sampling introduces additional noise into the estimator, so that the asymptotic variance-covariance matrix of the MSLE is inflated relative to the asymptotic variance-covariance matrix of the MLE, by a factor of $1+\frac{1}{S}$.[24] In the application of the MMNL model carried out in this analysis, the number of simulation sample draws is $S = 10$. This induces a loss of efficiency of the MSLE relative to the MLE of about 10 percent. Clearly, as more simulation sample draws are added, i.e. as S is increased, the relative efficiency loss is diminished, albeit at computational cost.

In case of the MMNL model, the point own and cross price elasticities can be estimated by $E_n\left[\tilde{\varepsilon}_{jj}(\mathbf{x}_i,\mathbf{z}_i;\hat{\beta}_{n,S})\right]$ and $E_n\left[\tilde{\varepsilon}_{jk}(\mathbf{x}_i,\mathbf{z}_i;\hat{\beta}_{n,S})\right]$, respectively, where $\tilde{\varepsilon}_{jk}$ is the simulated analogue to ε_{jk} which replaces the operator $\mathbb{E}_\theta$ by E_S. For the purpose of competition assessment, arc own and cross elasticities, typically associated with a 5 percent price rise, are of interest. In the MMNL model, define the α-percent arc price elasticity by

$$\alpha_{jk}(\mathbf{x}_i,\mathbf{z}_i;\beta) = \frac{\mathbb{E}_\theta\left[P_{ij}((\mathbf{x}_i\setminus p_k),(1+\alpha)p_k;\theta)|\mathbf{z}_i,\beta\right] - \mathbb{E}_\theta\left[P_{ij}(\mathbf{x}_i;\theta)|\mathbf{z}_i,\beta\right]}{\mathbb{E}_\theta\left[P_{ij}(\mathbf{x}_i;\theta)|\mathbf{z}_i,\beta\right]},$$

where $(\mathbf{x}_i\setminus p_k)$ denotes the vector $\mathbf{x}_i$ with the component p_k omitted. The displayed expression corresponds to an α-percent arc own price elasticity when $j = k$ and an α-percent arc cross price elasticity otherwise. Arc elasticities can readily be estimated by $E_S\left[\tilde{\alpha}_{jk}(\mathbf{x}_i,\mathbf{z}_i;\hat{\beta}_{n,S})\right]$, where, similarly, $\tilde{\alpha}$ is a simulated analogue to α.

[24] See, e.g., McFadden and Ruud (1994).

The accuracy of the estimation of the asymptotic variance-covariance matrix hinges on the computational and numerical complexity of the estimation problem and on the validity of the asymptotic convergence. An alternative approach to estimating the estimator variance covariance matrix, which some authors argue is more robust and, in any event, computationally more convenient, is to generate bootstrap replications of the estimator and approximate the true, but unknown sampling distribution of the estimator by the empirical distribution of the bootstrap replicates.[25] The analysis presented in this paper mimics this approach by generating 10 MSLEs on the basis of 10 samples of the entire data set and deducing a bootstrap MSLE as the sample mean and a bootstrap variance-covariance matrix as the sample variance-covariance matrix of these.[26] Although it is not fully explored in the present analysis, the bootstrap approach provides the additional advantage that the variability of derived estimates, such as elasticity point estimates, can be readily assessed. This compares favorably to the more cumbersome derivation of uncertainty estimates on the basis of the asymptotic distribution of the estimator, using the so-called delta method (Taylor series expansion).

6 Estimation Results

This section presents MSL estimation results, using the methodology described in the foregoing two sections. The first part reports and compares MNL and MMNL estimates based on the OSS data, and offers some insights from specification testing. The second part considers some derived estimates. The third part carries out the same analysis for non-OSS data.

[25] See, e.g., Efron and Tibshirani (1993).

[26] Strictly speaking, the bootstrap approach chosen here was less efficient than it could have been, because the bootstrap samples consisted of sub-samples of the entire population, without the typical replications. The loss in efficiency appears negligible, however, given the large sample and the results of some auxiliary runs on larger data sets that yield point estimates that are remarkably close to the mean bootstrap results.

6.1 Estimation Results for OSS Data

Table 3 presents MNL and MMNL point estimates, and for the latter bootstrap standard errors, as well as minimum and maximum bootstrap replicates.[27] The table also reports the values of the log-likelihood at the MLE for the MNL, and the value of the simulated log-likelihood at the MSLE for the MMNL. While informative, these numbers are not directly comparable because, conditional on the data, the former is a constant, while the latter is a random variable, due to the additional simulation noise. In other words, repeated simulation samples, conditional on the data, i.e. conditional on the $\{\mathbf{z}_i, i = 1, \cdots, n\}$, will generate a distribution of the value of the simulated log-likelihood function whose variance is due to simulation noise.

The MMNL estimation results exhibit several notable differences compared to the MNL estimates. While the average distance effects are comparable, the MMNL model exhibits a substantially larger average price sensitivity, which, next to the MMNL refinement of the MNL, leads to different predicted substitution patterns, as shown below.[28] Note that in the MMNL model the intercepts of the random coefficients on distance correspond to $-\exp(-1.2221) = -0.2946$; this implies, for example, that the expected distance coefficient for a two person household of social groups A-C is -0.2250, but it is substantially higher for households in social groups D and E. The trade-off between price and distance is further explored below. The MMNL model estimates of the standard deviation of the random price and distance coefficients suggest that there is considerable heterogeneity in consumers' distance and price sensitivity, and that, conditional on socio-demographics, on average more price sensitive consumer are less sensitive with regard to distance. Moreover, larger households appear to be more price sensitive than smaller ones, but less distance sensitive; the coefficient on car ownership in the distance coefficient is presumably poorly identified because the effect is picked up by the household size coefficient.[29] The MMNL model also appears to produce statistically significant and economically plausible fascia

[27] Net sales area is in 1000 m^2. The variable mission cost is defined as the interaction between spend and net sales area, scaled by $1e-08$.

[28] Recall that the MMNL price and distance coefficients are specified as $-\exp(a + b'\mathbf{z})$, where $\mathbf{z}$ is a vector of household level socio-demographics.

[29] Tobit regressions of number of cars on household size and other household characteristics exhibit a statistically significant and positive coefficient on household size, i.e. larger households tend to have more cars. It could also be hypothesized that larger households appear more sensitive to price because it is more likely that a household member commutes to work and carries out the household

effects, unlike the MNL model. The MMNL model picks up differences in valuations across socio-demographic groups, unlike the MNL, and if different fascias cater to different groups, then the MMNL model would be expected to identify this in terms of different fascia effects.

	MNL	std.error	MMNL	std.error	min	max
distance (intercept)	-0.2412	0.0023	-1.2221	0.1275	-1.5686	-1.0961
distance (hh size)			-0.1994	0.0109	-0.2207	-0.1789
distance (soc gr DE)			5.1311	0.1395	4.9730	5.4765
distance (cars$>$ 0)			-0.0000	0.0003	-0.0006	0.0000
distance (std dev)			0.5081	0.027	0.4840	0.5711
net sales area	-0.0181	0.0142	-2.2435	0.0649	-2.3745	-2.1880
mission cost	3.5214	0.2005	4.3626	0.3508	4.1468	5.3263
petrol	0.1809	0.0290	4.3121	0.0966	4.2028	4.4816
ATMs	0.2749	0.0528	0.1520	0.0080	0.1459	0.1723
restaurant	0.1765	0.0334	-0.7933	0.0614	-0.8792	-0.6427
toilets	0.4914	0.0508	3.1599	1.0068	0.3354	3.7773
price (intercept)	-7.6530	1.0640	4.4106	0.1200	4.1439	4.5683
price (hh size)			0.4056	0.0112	0.3870	0.4256
price (soc gr DE)			4.3542	0.2042	3.9143	4.6051
price (std dev)			1.0091	0.0298	1.0534	0.9471
Asda	16.4536	580.8978	1.8873	0.1892	1.7574	2.4038
M&S	2.08130	904.4186	-3.6754	0.7782	-4.2618	-1.5166
Morrisons	16.8094	580.8977	2.1289	0.6092	1.5108	3.8018
Sainsbury's	18.5671	580.8975	1.1866	0.1009	0.9655	1.3818
Somerfield	23.6604	580.8976	-5.0673	0.3143	-5.5801	-4.6356
Tesco	17.0485	580.8977	5.1998	0.814	4.6477	7.4424
Waitrose	22.6120	580.8975	0.9684	0.0777	0.7703	1.0476
distance-price cov			-0.3016	0.0118	-0.3232	-0.2829
log-lik.	-19179		-10769			

Table 3: ML and MSL coefficient point estimates; OSS data

shopping along the way. Unfortunately, the TNS data do not record the location of employment of the main shopper of the household and, hence, do not permit to empirically examine this possibility.

The MNL model, if appropriate, can be estimated more efficiently than the MMNL model because, in this case it would impose valid restrictions and it does not require simulation. Hence it is of interest to empirically examine whether the restrictions imposed by the MNL model, which is obviously nested within the class of MMNL models, hold in the sample. The null hypothesis of the MNL being appropriate can be tested by means of a Lagrange multiplier (LM) test. This test has the appealing property that its asymptotic χ^2 distribution does not depend on the mixing distribution. Details of the test procedure are given in McFadden and Train (2000). For the models considered in Table 3, the LM test statistic takes the value 438, which exceeds the 5 percent critical value of a χ^2_2 which is 5.99. Hence, the null hypothesis of no mixing (i.e. MNL) can be robustly rejected. It may also be worth noting that the adjusted R^2 statistic for the estimated MMNL model of 0.69 compares favorably to the adjusted R^2 statistic for the estimated MNL model, which is 0.44.[30] Strictly speaking, however, the same qualification applies with regard to comparability as in the case of the values of the log-likelihood functions evaluated at the estimators.

While the model appears to reproduce the sample market shares for the large fascias, it attempts to attribute some choices to fascias which were never chosen for OSS shopping in the sample, such as Coop and M&S; this appears to be predominantly at the expense of Sainsbury's predicted share. Table 4 provides a comparison of actual and predicted shares.

Fascia	actual	predicted
Asda	0.2348	0.2753
Coop	0	0.0395
M& S	0	0.0358
Morrisons	0.1642	0.1450
Sainsbury's	0.2021	0.1045
Somerfield	0.0424	0.0436
Tesco	0.3416	0.3096
Waitrose	0.0150	0.0133

Table 4: Actual vs. predicted shares, MMNL model

[30] The adjusted R^2 is calculated as $1-(L-k)/L_0$, where L is the likelihood function of the model with k parameters, and L_0 is the likelihood of a model with just an intercept.

6.2 Derived Estimates

On the basis of the MSLE, arc elasticities for a 5 percent price rise can be estimated, as outlined above. The resulting estimates permit to assess the competitive constraints that the various fascias exert on each other. Table 5 provides estimated arc elasticities. The table can be read along its rows, i.e. it gives the proportionate change of the predicted share of the column fascia in response to a 5 percent increase in the row fascia's price. For example, the top-left entry means that a 5 percent rise in Asda's price (index) leads on average to a reduction in the probability of consumers doing their OSS at Asda by almost one half, indicating quite elastic store level demand. For comparison, Table 6 provides MNL estimates of point own and cross price elasticities which by model design lack the power to distinguish differential substitution patterns arising from consumer preference heterogeneity.[31]

	Asda	Coop	MS	Morr.	Sains.	Somerf.	Tesco	Waitr.
Asda	-0.4606	0.0274	0.0241	0.2086	0.0439	0.0175	0.2830	0.0146
Coop	0.0046	-0.1616	0.0082	0.0079	0.0084	0.0083	0.0075	0.0071
M&S	0.0038	0.0075	-0.1596	0.0063	0.0093	0.0073	0.0066	0.0103
Morr.	0.0529	0.0253	0.0214	-0.2677	0.0320	0.0175	0.0588	0.0138
Sains.	0.0169	0.0208	0.0247	0.0241	-0.1901	0.0179	0.0286	0.0285
Somerf.	0.0039	0.0106	0.0101	0.0072	0.0093	-0.1363	0.0063	0.0085
Tesco	0.1210	0.0541	0.0505	0.1632	0.0900	0.0339	-0.2340	0.0464
Waitr.	0.0009	0.0026	0.0040	0.0016	0.0042	0.0024	0.0024	-0.1526

Table 5: MMNL estimated arc elasticities, 5 percent price rise of row fascia, OSS data

[31] While it may appear that the sum of cross price elasticity estimates exceeds the own price elasticity estimate for some stores, contrary to the prediction of microeconomic theory, this observation is somewhat misleading because the point estimates are random variables. In order to precise and test such an assessment, one would have to consider the variances and covariances of all the estimates involved in this comparison.

Fascia	own price elasticity	cross price elasticity
Asda	-0.3678	0.1781
Coop	-0.7105	4.71e-10
M&S	-0.7308	1.81e-10
Morrisons	-0.4537	0.1173
Sainsbury's	-0.4852	0.1505
Somerfield	-0.7888	0.0453
Tesco	-0.3359	0.2336
Waitrose	-0.7441	0.0372

Table 6: MNL estimated point elasticities

The MMNL estimates in table 5 suggest that Asda, Morrisons and Tesco are each others' strongest competitors, while Sainsbury is more constrained by Tesco and Morrisons than by Asda and itself, in turn, imposes a relatively weak constraint on them. The MNL model is not capable of delivering this more refined competitive assessment. Indeed, apart from the cross price elasticities being uniform across competitors, Table 6, together with Table 4, also shows that they are closely aligned with the fascia shares in the sample, e.g. Tesco's cross elasticity being 50 percent larger than Asda's.

The estimated model can also be used to empirically assess the extent to which consumers will choose more distant OSS shopping in response to a fascia's price rise. Table 7 shows the expected increment in distance, in terms of drive time, conditional on switching to a competing fascia in response to a 5 percent price rise of the row fascia. The second column displays the fraction of the row fascia's consumers that are predicted to switch to more distant stores, while the third column lists the fraction that is predicted to switch to more distant store with larger sales area than the biggest store of the row fascia in the choice set. The table suggests that only a relatively small fraction of consumers is diverted to stores farther away than the stores of the fascia that hypothetically raises price by 5 percent.

Fascia	Distance increment (in mins)	Fraction (in %)	Fraction to larger stores (in%)
Asda	8.1614	4.24	2.82
Coop	10.0336	4.15	2.56
M&S	7.2744	3.44	2.38
Morrisons	8.3299	4.68	3.35
Sainsbury's	6.7438	4.24	2.21
Somerfield	7.6990	9.18	5.65
Tesco	9.5841	8.56	5.21
Waitrose	8.1293	1.68	0.70

Table 7: Predicted substitution effects, OSS, 5 percent price increase

Similarly, the substitution pattern to large stores in response to a price rise can be estimated. Table 8 displays the respective proportions switching to stores of various size categories in response to a 5 percent price rise of the row fascia. Column (1) provides the row fascia's predicted market share after it hypothetically raises its price by 5 percent; column (2) the predicted market share loss, i.e. the difference between column (1) and the second column in Table 4; column (3) and column (7) are the ex post market shares of the row fascia's stores with net sales area exceeding $2000m^2$ and $1400m^2$, respectively; column (4) corresponds to the predicted loss in market share accruing at stores of at least $2000m^2$ net sales area; this can be compared with the row fascia's market share diverted to competitor stores with net sales area exceeding $2000m^2$ (column (5)) and $1400m^2$ (column (8)); columns (6) and (9) put diverted markets shares to competitors with at least $2000m^2$ and $1400m^2$ sales area in proportion to total lost market share, i.e. columns (5) and (8) in relation to column (2). The results in Table 8 suggest large proportions of diverted demand in response to a price rise accrue at large stores. On average, about two thirds accrue at stores with net sales area exceeding $2000m^2$, and for the big four UK grocers four fifth accrue at stores with net sales area of at least $1400m^2$

Fascia	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asda	14.85	-12.68	14.54	-12.37	8.49	66.96	14.78	10.34	81.56
Coop	3.31	-0.64	0.11	-0.02	0.43	67.88	0.35	0.52	80.90
M&S	3.01	-0.57	0.03	-0.00	0.37	65.56	0.38	0.44	77.51
Morrisons	10.62	-3.88	8.14	-2.95	2.82	72.79	10.30	3.18	81.85
Sainsbury's	8.47	-1.99	6.29	-1.48	1.29	65.10	7.31	1.54	77.30
Somerfield	3.76	-0.59	0.08	-0.01	0.38	64.45	0.44	0.46	77.12
Tesco	23.71	-7.24	14.90	-4.61	5.72	78.94	18.17	6.53	90.14
Waitrose	1.12	-0.20	0.24	-0.04	0.12	58.56	0.63	0.15	71.82

Table 8: Predicted substitution effects by store size, OSS data; in percent

6.3 Non-OSS Data

This subsection presents estimates based on the sample of non-OSS trips. Table 9 parallels Table 3 in the first subsection and summarizes MNL and MMNL point estimates, next to standard error estimates as described above.

	MNL	std.error	MMNL	std.error	min	max
distance (intercept)	-0.26880	0.0030	-1.1625	0.1189	-1.2698	-0.8402
distance (hh size)			-0.2266	0.0700	-0.4450	-0.1949
distance (soc gr DE)			5.0732	0.3065	4.5382	5.5564
distance (cars > 0)			0.0001	0.0005	-0.0008	0.0010
distance (std dev)			0.4896	0.0588	0.3298	0.5483
net sales area	-0.0387	0.0165	-2.1372	0.1369	-2.2448	-1.7962
mission cost	9.6093	0.7344	4.2533	0.1899	4.0103	4.5726
petrol	0.0708	0.0381	4.3551	0.3244	4.0516	5.2095
ATMs	0.0979	0.0537	0.1523	0.0070	0.1466	0.1708
restaurant	0.0812	0.0434	-0.7919	0.0154	-0.8229	-0.7640
toilets	0.0777	0.0529	2.8392	2.4955	-4.2338	4.2201
price (intercept)	-4.3474	0.7686	4.4615	0.0785	4.3886	4.6100
price (hh size)			0.3935	0.0169	0.3581	0.4205
price (soc gr DE)			4.3967	0.1530	3.9896	4.5620
price (std dev)			0.9935	0.0401	1.0466	0.9048
Asda	19.8140	751.5414	1.8231	0.0678	1.7003	1.9597
M&S	2.5765	1144.392	-3.9083	0.3189	-4.6720	-3.4679
Morrions	20.0350	751.5414	2.0171	0.1048	1.8600	2.2631
Sainsbury's	20.9548	751.5413	1.2049	0.0331	1.1565	1.2806
Somerfield	23.755	751.5413	-5.1998	0.6151	-6.9144	-4.7924
Tesco	19.9693	751.5414	5.0932	0.1695	4.7679	5.2790
Waitrose	23.2831	751.5413	1.0780	0.1766	0.9793	1.5597
distance price cov			-0.3049	0.0122	-0.3307	-0.2910

Table 9: ML and MSL estimation results; non-OSS data.

As one might expect for non-OSS trips, the implied arc price elasticities are estimated to be slightly lower than in case of OSS trips. Table 10 provides the respective derived MMNL estimates.

	Asda	Coop	MS	Morr.	Sains.	Somerf.	Tesco	Waitr.
Asda	-0.4220	0.0274	0.0238	0.1824	0.0421	0.0178	0.2327	0.0145
Coop	0.0051	-0.1624	0.0082	0.0078	0.0085	0.0084	0.0078	0.0071
M&S	0.0042	0.0076	-0.1603	0.0064	0.0095	0.0075	0.0068	0.0105
Morr	0.0548	0.0245	0.0212	-0.2598	0.0314	0.0178	0.0565	0.0138
Sains	0.0183	0.0212	0.0253	0.0245	-0.1875	0.0183	0.0291	0.0290
Somerf	0.0044	0.0107	0.0101	0.0074	0.0094	-0.1388	0.0066	0.0085
Tesco	0.1236	0.0546	0.0507	0.1529	0.0880	0.0345	-0.2233	0.0459
Wait	0.0011	0.0027	0.0043	0.0017	0.0044	0.0025	0.0025	-0.1529

Table 10: MMNL estimated arc elasticities, 5 percent price rise of row fascia, non-OSS data

Similarly, non-OSS is slightly more local, or more sensitive to distance, both in the MNL and the MMNL model. This implies somewhat smaller expected incremental travel distance in response to a 5 percent price rise, conditional on switching. Table 11 provides comparators for non-OSS to Table 7.

Fascia	Distance increment (in mins)	Fraction (in %)	Fraction to larger stores (in%)
Asda	8.5246	4.40	2.50
Coop	9.3949	3.92	2.14
M&S	7.8290	3.80	2.14
Morrisons	9.2949	4.52	2.38
Sainsbury's	5.5781	5.23	3.57
Somerfield	7.8619	8.68	5.83
Tesco	6.7482	9.27	6.42
Waitrose	7.1613	0.83	0.59

Table 11: Predicted substitution effects in terms of distance and size, non-OSS

Finally, substitution patterns with respect to store size can be inferred for non-OSS trips, comparable to the results for OSS trips in Table 8 above. For non-OSS trips, the corresponding derived estimates are reported in Table 12, with column definitions as for Table 8.

Fascia	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asda	15.08	-11.01	14.75	-10.75	7.30	66.33	15.01	8.95	81.26
Coop	3.47	-0.67	0.11	-0.02	0.45	67.38	0.37	0.54	80.75
M&S	3.20	-0.61	0.03	-0.01	0.40	65.02	0.40	0.47	77.24
Morr	11.01	-3.87	8.39	-2.93	2.79	72.16	10.68	3.15	81.50
Sains	9.02	-2.08	6.66	-1.55	1.33	64.10	7.75	1.60	76.77
Somerf	3.94	-0.63	0.08	-0.01	0.41	64.19	0.47	0.49	77.02
Tesco	24.77	-7.12	15.43	-4.50	5.60	78.63	18.96	6.38	89.54
Wait	1.24	-0.22	0.24	-0.04	0.13	58.02	0.67	0.16	71.63

Table 12: Predicted substitution effects by store size, non-OSS data; in percent

A comparison of Tables 8 and 12 suggests that Asda and Tesco lose a slightly larger share of the OSS market than in the non-OSS market in response to a hypothetical 5 percent price rise, while the opposite holds for for smaller retailers such as Coop, M&S, Sainsbury's and Somerfield. For Morrisons, the estimated effect is about the same for the two types of shopping. The previous finding that large proportions of OSS is diverted to stores with large net sales area appears to also hold for non-OSS.

In summary, the results delivered by the analysis provide evidence of heterogeneity in consumers sensitivity to price and distance attributes of the relevant retail offering, controlling for other observable attributes of choice alternatives and taking account of the consumer's socio-demographic profile. Poorer consumers are found to be more price and distance sensitive than richer consumers; larger households are more price sensitive, but, being more likely to own a car, are less sensitive to distance; unobserved consumer characteristics that are likely to govern their sensitivity to distance, e.g. health and physical mobility, are found to be negatively correlated with those that govern their sensitivity to price.

The analysis also presents own and cross price elasticities of fascia choice probabilities. These suggest that Asda, Morrisons and Tesco are each others' strongest competitors, while Sainsbury is more constrained by Tesco and Morrisons than by Asda and itself, in turn, imposes a relatively weak constraint on them. Moreover, the estimated model suggests that, in response to a fascia's price rise, only a relatively small fraction of consumers is prepared to incur higher travel costs conditional on switching to competing fascias, between 1 and 9 percent, regardless of shopping type; the induced travel costs arise from more distant shopping, with increments estimated to range from 6 to 10 minutes for OSS, and from 5.5 to 9 minutes for non-OSS. Similarly, conditional on switching to a competitor in response to a fascia's price increase, the estimated model suggests that on average two thirds of the diverted consumption goes to large stores, with net sales area above 2000 m^2, and for the big four UK fascias four fifth is diverted to stores with net sales area above 1400 m^2; only a comparably small fraction is predicted to turn to smaller stores. This suggests that store size is a defining strategic variable with regard to a fascia's design of the product offering. These findings appear robust with respect to the two definitions of shopping employed in the analysis, OSS and non-OSS.

7 Concluding Remarks

This paper provides a micro-econometric framework for geographic antitrust market definition and competitive assessment, embedded into the classical hypothetical monopolist test paradigm. Focussing on its demand-side component, it presents a demand model in an application for UK grocery retailing that captures the essential trade-off between distance and pecuniary costs. It builds on a general random utility model for fascia choice that allows for observed and unobserved heterogeneity in consumer preferences. It identifies socio-demographic household characteristics that drive price and distance sensitivity in one-stop and non-one-stop grocery shopping. The analysis suggests a trade-off between sensitivity with respect to price and distance, with poorer households being more sensitive to both and larger households being more sensitive to price, while being less resistant to more distant shopping. With regard to competition relevant insights, this analysis provides evidence that, in response to a fascia's hypothetical price rises, most consumers who switch to a competitor fascia are likely to switch to one with larger net sales area, but only a small fraction of those who switch are expected to travel further to do their grocery shopping. These findings appear robust with respect to the definition of shopping employed in the analysis.

Future work will use this model, nested within the framework of Section 2, to combine it with cost or margin data in order to define hypothetically monopolizable markets, similar to Davis (2006) and Smith (2004).

A Construction of Price Measures[32]

The price measure is based on the responses to main parties questionnaire (MPQ) question 58, in which the CC defined about 220 product categories and asked parties to provide store-level prices for their top-selling product (SKU) in the particular category (top-selling across all stores of the party, e.g. for Tesco top-selling across all Tesco fascias including One-Stop).

This implies that, for many product categories, the given prices are not for the same product (e.g. for ice-cream one party gives the Häagen-Dazs price and another gives the own-label price.)

1) Selection of component goods

For the six product definitions covered in the Brands-basket, however, (almost) all parties gave prices for exactly the same product (e.g. for lemonade the price of Schweppes Original Lemonade.)

The larger baskets were determined by selecting those 47 out of the 220 product definitions that will not include well-known brands (KVI) - these product definitions mainly relate to basic groceries like flour, fruits, vegetables, meat, etc. However, most stores did not seem to sell all 47 products in this basket. Therefore, the number of products in the basket was iteratively reduced by those products with the largest shares of missing values across stores, to arrive at basket sizes of 33, 16 and 12 products. Therefore, by definition store coverage of the respective price measure increases when the number of products in the basket decreases.

Since most stores seem to sell the six branded products, these were added to the above 16- and 12-product baskets to increase their product coverage without loosing too many stores.

2) Weights

[32] With thanks to Jonathan Beck for contributing this section on the construction of price measures.

In the "Plain" version or the price measure, the posted prices of the component products are simply added. Thus each has the same weight.

In the "Weighted" version of the price measure, the total revenue generated by sales of the component goods were calculated across all stores (national GBP-sales of the component goods). Each product weight in the basket is then its share in total basket revenues (national GBP-sales of this product divided by national GBP-sales of all products in the basket). Thus the price of bananas tends to have a larger weight in the price measure in which it is included, while the price of cabbage tends to have a small weight.

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