Multi-Category Competition and Market Power: A Model of Supermarket Pricing*

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Abstract

In many competitive settings consumers buy multiple product categories, and some prefer to use a single firm or location, generating complementary cross-category price effects. To study pricing in supermarkets, a form of retail organization where these effects are internalized, we develop a multi-category multi-store demand model and estimate it using UK consumer data. This class of model has been used widely in theoretical analysis of retail pricing. We quantify cross-category pricing effects and find that internalizing them substantially reduces market power. We find that single-firm shoppers have a stronger pro-competitive impact than multi-firm shoppers because they generate greater cross-category effects.

JEL Numbers: L11: L13: L81

1 Introduction

In many competitive settings consumers buy multiple categories and find it convenient to obtain them all from a single store, location, or firm. This shopping behavior can generate complementary cross-category pricing effects, as an increase in the price of one category may lead a consumer to transfer away all his category purchases. The magnitude of cross-category pricing effects depends on consumer shopping behavior: a consumer that prefers

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to purchase all categories at a single store may generate larger cross-category effects than a shopper that is willing to use multiple stores, as the latter can switch store only for the category affected by a price change and not for other categories.

Whether sellers internalize such cross-category effects depends on the organization of supply.[1] In supermarket organization there is a maximal level of internalization, as a single seller sets prices for all categories sold at the same store. In malls, streets, or public market places, on the other hand, separate categories have independent vendors—e.g. butchers for meat, bakers for bread, etc.[2] There are some cases with incomplete levels of internalization, such as stores that lease a section of their floor space, and delegate pricing, to an independent category seller.[3]

It has long been recognized that the internalization of complementary pricing effects can substantially mitigate market power. In the monopoly case in Cournot (1838) a single seller of two strictly complementary categories sets an overall Lerner index that is half as high as would arise with two independent sellers. In oligopoly settings—where categories sold by any firm are pricing complements because of the costs to shoppers of buying from multiple firms—internalization can greatly intensify price competition (see Nalebuff (2000), Cabral and Villas Boas (2005)).[4]

The market power of supermarkets is an issue of widespread interest. The industry's revenues are a large share of GDP and its behavior affects many interest groups from consumers to suppliers.[5] The analysis of pricing in the supermarket industry has typically been conducted at two alternative levels. The first is the level of the individual supermarket category, e.g. breakfast cereals, alcoholic drinks, etc., where there are concerns that prices are set inefficiently, either too high because of market power (see Hausman et al. (1994), Nevo (2001), Villas Boas (2007), Bonnet and Dubois (2010)), or too low because of a predatory intent or a negative consumption externality (see Griffith et al. (2010)). The second is the level of the retailer as a whole, setting prices across a range of categories (see for example Chevalier et al. (2003) and Smith (2004)). This level is appropriate for antitrust investigations into supermarket competition (see Competition Commission [CC] (2000, 2008)) and retail merger cases such as the proposed merger of Whole Foods and Wild Oats (considered

[1] A well-known example outside of retailing is the selling of component parts for an aeroplane. The proposed GE-Honeywell merger would have resulted in a single seller of two categories (aircraft engines and avionics) and the consequences of internalization of complementary cross-category effects was a central issue in the European Union's approach to the merger. See Nalebuff (2009).

[2] We use the term category or product category to refer to a group of similar product lines that are close substitutes, as in these examples.

[3] For example, retailers such as Sears and Walmart sometimes rent out space within their stores to independent sellers, in return for a rental payment (see Wall Street Journal Sept. 22, 2010). These arrangements are sometimes referred to as "stores within a store" or "in-store concessions".

[4] This is closely related to the finding from the compatibility literature that two multi-product firms may set more competitive prices if their products are incompatibile—so that consumers must buy only from one firm—than when they are not (see Matutes and Regibeau (1988), Economides (1989)).

[5] For example in the UK the supermarket industry's revenues were £110.4bn in 2007 (see Competition Commission (2008), paragraph 3.2) which is about 8% of GDP.

by the Federal Trade Commission [FTC]).[6] At this level there has been much interest in the growth of large retail firms such as Walmart and Carrefour, see Basker (2007), Jia (2008), and Holmes (2012). Sometimes public policy has been introduced to protect traditional forms of retail organization such as streets and market places, which do not internalize cross-effects, by curtailing the growth of supermarkets: e.g. in France a law (*Loi Raffarin,* 1996) imposed restrictions on new supermarkets for this purpose. For pricing analysis at each of these two levels it is important to understand the extent to which the internalization of cross-category effects mitigates market power.

A related issue, in the supermarket industry, and more generally, is whether one-stop shoppers (who use only a single store) constrain market power more than multi-stop shoppers (who use multiple stores). One possibility is that one-stop shoppers—known in some contexts as "core" or "single-homing" shoppers—have the greater pro-competitive impact, because they generate a relatively large cross-category effect when they change store. The opposite can also be argued, however: multi-stop shoppers may have the greater pro-competitive effect as they find it easier to substitute any individual category between stores. This has been an important question in prominent antitrust investigations. In the UK's CC inquiries into the supermarket industry, some firms claimed that multi-stop shoppers have the greater pro-competitive impact as they can easily substitute to a wide range of possible outlets. These firms argued that "since supermarkets could not price discriminate [in favor of multi-stop shoppers], these other outlets collectively placed a competitive constraint on the grocery retailer's offer" and that multi-stop shoppers "effectively [...] determined supermarket prices across the board." See CC (2000, paragraph 2.31). The same argument was made in the US in the proposed Whole Foods/Wild Oats merger, where the parties to the propsed merger argued that many of their customers "cross-shop" in a wide range of other firms, buying different categories from different stores, and these multi-stop shoppers constrained prices more than one-stop (or core) shoppers. In these investigations the authorities had to decide whether to focus on promoting competition between retailers that are substitutes for one-stop shoppers, or on competition between retailers that are combined by multi-stop shoppers.[7]

In this paper we have two main goals. First, we develop a multi-store multi-category model of consumer demand, that belongs to a class of models used widely in the theoretical literature to analyze retail pricing, and estimate it using household-level data on shopping choices at consumer-store-category level. Recent demand models used to study retail market power have not considered cross-category externalities, despite their prominence in the

[6]FTC v. Whole Foods Markets, Inc., 533 F.3d 869 (D.C. Cir. July 29, 2008).

[7]In both cases there was a debate as to whether one-stop (core) or multi-stop (cross-shopping) customers were the group that constrained supermarket prices the most, with implications for whether a narrow or wide definition of the market was appropriate for competition analysis. According to one of the main firms in the CC investigation "it was the marginal shopper—with the greatest tendency to migrate—who determined prices" and this firm claimed that it "had a high proportion of secondary shoppers and could not be indifferent to them in terms of its price setting." (See CC (2000, paragraph 4.68)).

theoretical literature. Second, we use the model to study two policy-relevant issues in retail pricing (as mentioned above): (i) the implications of the internalization of cross-category externalities for market power and (ii) the relative impact of one-stop and multi-stop shoppers on equilibrium prices. We define categories to correspond to product groups sold by traditional independent sellers of grocery products in streets and public market places (butchers for meat, bakers for bread, etc.) in order to analyze cross-effects that are internalized in supermarket organization but not in a well known alternative organization of supply.

In the model each consumer decides whether to use a single store or multiple stores for their category purchases in a given shopping period. For each category a consumer makes a discrete choice of store, and a continuous choice of how much to buy. There is differentiation between stores at two levels. The first is at individual category level: the consumer views stores as being different for any category. We allow this differentiation to be partly vertical, reflecting differences in the average quality of stores for any category, and partly horizontal, reflecting variation in individual consumer preferences. The second level of differentiation is at the overall shopping level: each consumer views the fixed costs of shopping at each store differently because of spatial variation in consumer location. For any consumer the benefits of multi-store shopping—allowing the consumer to go to the best store for each category—must be weighed against the fixed costs of using multiple stores.

There are two main econometric challenges in estimating the taste parameters that enter category-specific demands. First, a significant number of zero expenditures are observed at category level, so that there are binding nonnegativity constraints in the consumer's continuous category demand problem. Second, given that a consumer's unobserved category-store tastes influence both his choice of store and his category demands, the consumer's unobserved tastes are not independent of the observed characteristics of the stores the consumer selects, so that any method that estimates the continuous category demands by conditioning on the consumer's store choices may result in inconsistent estimates. To overcome both these problems we estimate the consumer's utility parameters in a single step which jointly models both the consumer's nonnegativity constraints and his combined discrete-continuous choice of store and category demand. We use a Generalized Method of Moments (GMM) approach that matches simulated discrete and continuous predictions of the model to the data.

The estimated parameters imply complementary pricing effects between categories sold by the same retailer. We estimate the Lerner index of market power implied by these elasticities in Nash equilibrium, using the retailers' first order pricing conditions. We find that ignoring cross-category effects and analyzing each category in isolation can result in market power being overestimated substantially: accounting for complementary cross-category effects reduces the estimated Lerner index by more than half for most categories and firms. To quantify the externality between product categories, that is internalized by a supermarket, we compute the implicit marginal (Pigouvian) subsidy per unit of output that must be offered to an independent category seller to ensure it does not increase prices relative to the observed levels (set by supermarkets). We find that the externality is about 0.50 of the price of the category (on average across firms). This externality is analogous to the "pricing pressure" concept that measures the effects of a merger, introduced in Farrell and Shapiro (2010).[8] The absolute value of our estimates are larger than standard externality levels used to flag an adverse merger, i.e. our estimates indicate that supermarket organization mitigates market power significantly.[9]

To compare the relative competitive implications of one-stop and multi-stop shoppers we consider a series of unilateral category-firm price increases and compare the impacts on the two shopper groups. We find that two-stop shoppers have greater own-category effects, as they change store more readily for the affected category than one-stop shoppers, but they also have lower cross-category effects. We disaggregate the firm's profit effect into the component earned on each shopper group, and find that a small price increase (starting from equilibrium prices) typically reduces profits from one-stop shoppers, and increases profits from multi-stop shoppers, which indicates that one-stop shoppers have the greater pro-competitive impact on supermarket prices. This is consistent with the approach ultimately taken by the CC and FTC in the cases mentioned above, where the focus of the authorities was on maintaining a competitive market for core shoppers.

The theoretical literature makes extensive use of a multi-store multi-category modelling framework to study retail pricing. Some papers in this literature impose one-stop shopping (Stahl (1982), Beggs (1992), Smith and Hay (2005)) while others model the multi-stop shopping decision (Klemperer (1992), Lal and Matutes (1994), Armstrong and Vickers (2010), Chen and Rey (2012), and Rhodes (2015)). The empirical literature on retail market power—in contrast to the theoretical literature, as noted in Smith and Thomassen (2012)—has typically not incorporated cross-category externalities. We adapt the multi-store multi-category theoretical framework for empirical analysis. We develop a model that is multiple-discrete-continuous, in that the consumer can choose one or more discrete store and makes a continuous non-negative choice of quantity for every category. We build on the existing literature on multiple-discrete choice (see Hendel (1999), Dube (2005), Gentzkow (2007)), and discrete-continuous choice (see Dubin and McFadden (1984), Haneman (1984)).[10] Our multi-category multi-store model brings together the empirical literature that measures mar-

[8] Supermarket organization (or any form of retailing in which cross-category effects are internalized) can be interpreted as a merger of independent category sellers in a shopping location (see Beggs (1992)). This leads to *downward* pricing pressure, because the categories have complementary cross-price effects, the reverse of the standard upward pricing pressure that follows from merger of substitutes.

[9] The presence of large external effects between product categories at a retail location is consistent with the theoretical literature on multi-category sellers, as discussed in Nalebuff (2000), and supported empirically by a study of rental payments in shopping malls in Gould et al. (2005), which found that mall owners offered large rent subsidies to stores that generate a positive externality (by drawing consumers to the mall) for other stores in different product areas. The marketing literature also finds that cross-effects between categories are empirically important, e.g. Vroegrijk et al. (2013).

[10] The discrete-continuous literature, Dubin and McFadden (1986) and Haneman (1984), considers a single discrete and a single continuous choice in which zero is not allowed. We generalize to allow for multiple continous choices. As we allow for zeros in the continuous choices the paper is related to the literature on demand estimation subject to nonnegativity constraints, notably Wales and Woodland (1982).

ket power for a single supermarket category (e.g. Nevo (2001) and Villas Boas (2007)), with the literature on spatial competition between retail outlets in which the choice of category is not modelled (e.g. Smith (2004), Davis (2005) and Houde (2012)).

The rest of the paper is organized as follows. In Section 2 we discuss relevant features of the market and the data. We discuss the model in Section 3 and estimation in Section 4. We report estimates in Section 5 and in Section 6 we analyze supermarket pricing.

2 The Market and the Data

Supermarkets became widespread in the US and UK in the mid 20th century. Until then broad grocery categories had been sold by independent sellers in streets, public market places, or through direct delivery to households. The categories used in this paper are defined to correspond approximately to the products sold by these traditional vendors. They are shown in Panel A of Table 1. Thus products in the Bakery category are sold by a traditional baker, Fruit & Vegetables by a greengrocer, Drink in a liquor store, etc. This definition allows us to analyze cross-effects that are internalized by supermarkets but not in a familiar alternative organization of supply.

To analyze shopping behaviour we use data from TNS Superpanel (now run by Kantar), which records the grocery shopping of a panel of households in Great Britain. Our sample is for the three-year period October 2002-September 2005.[11] The data are recorded by households, who scan the bar code of the items they purchase and record quantities bought and stores used. The grocery items include all products in the categories listed in Table 1 including those sold in irregular weights such as fruit, vegetables and meat. Prices of items bought are obtained from the expenditure and quantity information that the household records, and cashier receipts are used to confirm these prices. Demographic and location information for each household is recorded annually. We treat the household as a single decision-making agent and we use the term consumer to refer to this agent.

We adopt a week as the shopping period in which the consumer plans his shopping. A weekly shopping frequency was found in survey evidence in CC (2000, paragraph 4.77 and Appendix 4.3) in which 982 respondents were asked the question: "How often do you carry out your main grocery shopping?" A large majority (70%) reported a weekly frequency with 14% less frequently and 16% more frequently. We aggregate store choices and expenditures to the weekly level and assume that decisions on how much to spend in each store are made for the whole week.

Table 1 aggregates consumer expenditure to the weekly level. The table includes all consumer-week observations in which the consumer has positive grocery expenditure in at least one store. Panel A gives expenditure at category level and shows that a substantial proportion of consumers have zero expenditure in a given week. This may be because

[11] 26,191 consumers participated in this period with an average of 67.6 weeks recorded per household.

Table 1: Demand Categories: Weekly Per-Household Statistics

A: Weekly Category Expenditure				
		Expenditure (£/week)		Zeros
Category	Illustrative products	Mean	St. Dev.	(share)
Bakery	Bread, Cakes, Desserts	3.94	3.81	0.09
Dairy	Cheese, Yoghurt, Butter	3.61	3.61	0.18
Drink	Wine, Spirits, Lager, Cola	5.50	9.75	0.31
Dry Grocery	Breakfast Cereals, Confectionery, Coffee	6.30	6.06	0.10
Fruit & Vegetables	Fruit and Vegetables (including frozen)	7.90	6.85	0.06
Household	Pet Food, Detergents, Toilet Tissues	6.10	7.23	0.22
Meat	Ready Meals, Cooked Meats, Fresh Beef	11.44	10.59	0.07
Milk	Low Fat Fresh Milk, Organic Fresh Milk	1.37	1.53	0.28
All categories		46.16	32.2	0.00

B: Weekly Overall Use of Stores	Mean	St. Dev.
All Households		
One store for all weekly spending (1/0)	0.53	0.50
One store for all weekly spending over £2 (1/0)	0.57	0.50
Households using > 1 store/week:		
Expenditure share in 1st store by overall spending (store A)	0.70	0.18
Expenditure share in 2nd store by overall spending (store B)	0.25	0.06
C: Intra-Category Store Use, Households using > 1 stores/week	**Mean**	**St. Dev.**
Share of category spending in 2nd store for category from {A,B}:	0.10	0.15

D: Category choices, Households using > 1 stores/week

1st and 2nd Store	Tesco/ASDA 1st store for category (1/0)			
(by overall weekly spending)	Bakery	Drink	H'hold	Meat
Tesco & Aldi	0.66	0.40	0.58	0.68
Tesco & M&S	0.45	0.85	0.94	0.39
ASDA & Aldi	0.62	0.45	0.57	0.70
ASDA & M&S	0.47	0.84	0.94	0.42

Notes: Taylor Nelson Sofres (TNS) Superpanel survey of households in Great Britain, October 2002-September 2005. Illustrative products in each category are from TNS's list of 269 granular product classifications. The full list of products in each category is shown in Appendix A. The statistics are calculated at household-week level (i.e. we aggregate expenditures to the week) for each week a household is observed to make a positive expenditure. The table uses the full sample which has 26,191 consumers and 67.6 weeks (with expenditure observations) per consumer. In Panel B the (1/0) dummies take the value 1 if the consumer uses one store in the week and 0 if the consumer visits more than one store. In Panel D the the (1/0) dummies take the value 1 if the consumer's main store (by expenditure) for the category is ASDA or Tesco; the figures in the panel are averages for two-stop shoppers at the two stores listed the first column.

consumers do not wish to purchase all categories every week or because they buy from non-supermarket sellers (e.g. doorstep deliveries are sometimes used for milk in Great Britain).

Panel B shows that 53% of consumers use only one store (one-stop shoppers), and this does not increase much when minor expenditures are excluded. For the 47% of consumers using more than one store we note two features of the data. First, shopping outside the top two stores (by spending) is minimal (Panel B); consequently we hereafter analyze the consumer's choice of up to two stores and for simplicity refer to consumers using more than one store as two-stop shoppers. Second, within any individual category, two-stop shoppers concentrate their expenditure in just one store (the identity of which differs by category): only about 10% of their expenditure within any category is allocated to the store with the lower expenditure for that category, out of the consumer's top two stores (Panel C).

Panel D illustrates how two-stop shoppers allocate their spending between firms. Consider four firms. ASDA and Tesco are traditional supermarkets that are relatively attractive to one-stop shoppers; they operate large stores that stock a wide range in all categories. The other two firms are, on the other hand, relatively attractive to two-stop shoppers: Aldi is a low-price limited-range discounter, and M&S specializes in premium fresh food. The table considers four groups of two-stop shoppers defined by their chosen store pair: ASDA & Aldi, ASDA & M&S, etc. It shows the proportion of two-stop shoppers that use the first-named firm in each pair as their main store (by spending) for the category: e.g. 66% of Tesco-Aldi shoppers select Tesco for Bakery, and 60% of the same group of shoppers select Aldi for Drink. A pattern emerges in which the discounter firm (Aldi) is strong relative to traditional supermarkets (ASDA and Tesco) in categories where products tend to be non-perishable (e.g. Drink and Household goods), but less strong in perishable categories (e.g. Bakery and Meat). The premium firm (M&S) has the opposite pattern: strong for perishables and weak for non-perishables.[12]

In the rest of this section we discuss the construction of the data used in the consumer model. To obtain consumer choice sets we match each consumer to local stores using a store dataset from the Institute for Grocery Distribution (IGD), which includes the floor space (sales area), firm, and Post Code of all supermarket outlets in Great Britain. To locate consumers and firms we use Post Code information in the consumer and store data.[13] We assume that the consumer's choice set is his nearest 30 stores.[14] We model consumers as

[12] Supermarkets appear to think about their product offering at a category level when determining price and quality positions: they often define management jobs by category, and thus organize product selection and and pricing decisions this level. Supermarkets, however, unlike a retailer in a street or mall, internalize the profit effects of these choices on other categories. (For more discussion of these points, see CC(2008), Appendix 8.1, paragraphs 10-13).

[13] Geographic coordinates for every Post Code in Great Britain are available from the Postcode Directory, produced by the UK's Office for National Statistics. For each store in the IGD data we therefore have an exact location. The location of each consumer is known at a slightly coarser level (to preserve anonymity), namely the Postal Sector. This is not a substantial loss in precision, however: Postal Sectors are small neighborhood-sized areas of a few thousand households. We locate each consumer at the average coordinates of the residential Post Codes in their Postal Sector (listed in the Postcode Directory).

[14] The store data include all stores operated by supermarket chains. Where a chain operates more than

Table 2: Consumers and their Choice Sets

A: Household Variable			Mean	St. Dev.
Household size			2.67	1.34
Household Weekly Income (£) per Head			227.30	116.19
Spending per Week (£)			41.11	29.67
B: Variation between choice sets	Dist (km) to nearest firm f store			
Firm f	Lower quartile	Median	Upper quartile	No firm f in choice set
ASDA	2.54	5.07	13.88	16.1%
Tesco	1.09	2.05	4.09	0.4%
Discounter [Aldi, Netto, or Lidl]	1.89	3.92	10.34	11.4%
M&S	2.24	4.22	9.92	9.6%

Notes: Random sample of 2000 households used in estimation. In Panel B households are sorted in ascending order of distance to nearest store of the indicated firm; e.g. lower quartile is the 500th (from shortest) distance. The firms in Panel B differ in their price positions (e.g. ASDA and Discounters have relatively low prices).

choosing either one or two stores per week, so that a choice set of 30 stores implies 465 possible store pairs and singletons. For each store that is chosen by a consumer the TNS survey indicates the firm (e.g. ASDA, Tesco, etc.) and for stores operated by the main firms it usually records the Post Code.[15] The Post Code is known for 70% of store choices. When it is not known we assume the consumer goes to a store in the choice set operated by the firm they choose.[16]

We compute price indices at firm level. This aligns with the policy of firms in the period of the data, which is to set national prices that do not vary by store location. This policy is convenient as we can use prices observed in any transaction in a given week to compute the firm's (national) price index; we use the full sample of transactions in the TNS data. We aggregate over two hierarchical levels, following standard practice in price index construction. At the lower level we compute a price index for a series of narrowly defined product groups, listed in Appendix A (e.g. shampoo is a product group in the Household category), using quantity from the transactions data to weigh the individual products. At the upper level we compute a price index for each category (e.g. Household) using sales revenue from the transactions data to weigh the lower-level price indices. At both levels the

one very small store in any choice set—defined as having a sales area of less than 3000 square feet, which corresponds to outlets of convenience store size—we use only the nearest of these stores to the consumer; this avoids choice sets from filling up quickly with very small stores.

[15] The Post Code is recorded for most ASDA, Morrison, Sainsbury, Tesco, Waitrose and Somerfield stores.

[16] In many cases there is just one candidate store; in cases with more then one we pick one at random, using empirical probability weights that depend on distance and store size. The probability weights are based on empirical frequencies. We use the store's predicted probability (conditional on choice of firm) from a reduced form multinomial logit model of store choice, estimated using the sample of 2000 consumers, for consumers whose store choices are known. The probability is a function of two variables: store size and distance. (An alternative approach which is also feasible is to aggregate the model's predictions to the firm level—for observations when the chosen firm is known but not the specific store—and estimate the model accordingly; see Smith (2004)).

Table 3: Descriptive Statistics by Supermarket Chain for the Consumer Sample

A: Store Characteristics			Store Floor space (1000 sq. ft.)		
		Number of Stores	Mean	St. Dev.	Mean Price
ASDA	Big Four	273	45.3	14.23	1.01
Morrison	Big Four	351	30.3	8.54	1.05
Sainsbury	Big Four	522	28.7	17.11	1.16
Tesco	Big Four	1,380	17.01	21.07	1.10
M&S	Premium	316	8.40	1.96	1.84
Waitrose	Premium	166	19.13	9.18	1.42
Iceland	Frozen	689	4.86	1.14	1.14
Aldi	Discounter	263	7.85	1.40	0.85
Lidl	Discounter	115	9.55	2.82	0.79
Netto	Discounter	133	6.53	1.59	0.78
Small Chains	Other	3,511	5.58	5.33	1.23

B: Prices by Category	Bakery	Dairy	Drink	Dry	Fr,Veg	Hhold	Meat	Milk
Mean	1.168	1.206	1.150	1.156	1.322	1.078	1.121	1.127
St. Dev. (Between stores)	0.185	0.163	0.241	0.220	0.238	0.190	0.196	0.072
St. Dev. (Within stores)	0.033	0.033	0.023	0.017	0.036	0.022	0.023	0.040

Notes: Statistics are for 7719 the distinct stores in choice sets of the 2000 sampled consumers. The mean price in Panel A averages across 8 categories and 156 weeks in the sample period. Between- and within-store standard deviations in Panel B use store-week prices for all 156 weeks. Prices for each category are normalized to 1 for ASDA in the first week of the sample.

weights are fixed over time to ensure that intertemporal changes in the price index reflect changes in prices rather than composition effects in the weights; at the upper level weights are fixed across firms so that differences between firms in the price index are driven by prices rather than firm-specific weights, which avoids selection bias from the possibility that the consumers selecting a particular firm have tastes that differ from the population.[17] The weights are computed separately for eight demographic groups, depending on household size and occupational class, to allow different types of consumers to have different price indices depending on their tastes. The resulting prices are at a firm-category-week-demographic level. Further details are in Appendix B.[18]

To estimate the model we draw 2000 consumers and pick a week at random for each.[19]

[17] At the lower level it is not possible to fix weights across firms as some products are firm-specific (e.g. private-label shampoo brands). See Appendix B for details.

[18] According to the CC the major firms in the market adopted the practice of national pricing during the period of the study, the exceptions were Co-op and Somerfield which have small market shares, see CC (2008, p498-501). We allow for the possibility that prices depend on store size (as opposed to store location) for the Big Four firms (which have more size-heterogeneous stores) by computing two price indices depending on whether the floorspace of the store is over 40,000 square feet; in practice we find the difference by store size is insignificant. We compute a price index for eight other firms (namely Aldi, Co-op, Iceland, Lidl, M&S, Netto, Somerfield, Waitrose) and a further price index representing prices in a group of very minor chains. This results in 17 firm level price indices for each of 8 demographic groups and 156 weeks, yielding 21,216 prices for each category.

[19] To avoid households uncommitted to the data sampling process, we restrict the sample to households

We aggregate expenditure to store-category-week level for each household. Table 2 presents statistics for the sample of 2000 consumers and their choice sets. Panel A reports variables at household level.[20] Panel B illustrates one of the main sources of identification in the model: the variation in consumer choice sets. The first three columns give quartiles for the distances to four selected firms (or firm types) that are associated with different price and quality offerings: ASDA, Tesco, any Discounter (Aldi, Lidl or Netto), and M&S. These columns show a wide variation in the distances consumers have to travel to reach each of these firms—e.g. the distance to the nearest ASDA, a firm associated with relatively low prices, has a lower quartile of 2.54km and an upper quartile of 13.88km.

Table 3 presents statistics at store level for the 7791 stores that appear at least once in the choice sets of the 2000 consumers. Panel A allows us to see how the main firms differ. We classify the firms into a number of groups. ASDA, Morrisons, Tesco and Sainsbury (widely called the Big Four) are traditional supermarkets with the largest stores and a high market share. The next group, M&S and Waitrose, which we call Premium firms, have an emphasis on high quality fresh food. The next three firms—Aldi, Lidl, and Netto— are widely referred to as as Discounters and sell a limited range of grocery products at low prices. One firm (Iceland) emphasizes frozen food. The remaining firms ("Others") are smaller chains with a low market share (namely Co-op, Somerfield, and a group of very minor chains). Panel B presents price information at category level: the mean price is reported for each category along with the between-store and within-store standard deviation. The between-store variation is driven mainly by price differences across firms and the within-store standard deviation is due to price variation over time.

3 Theory: Utility and Demand

3.1 General Description of the Model

We now develop a model of multi-category shopping. In a given week consumer i makes a shopping choice c which comprises either one or two stores from the consumer's set of stores $\mathcal{J}_i$. We write choice c as the set of stores in the shopping choice: e.g. if c has two stores j and j' then c is the pair set $c = \{j, j'\}$ and if it has one store j it is the singleton

that participated for at least 10 out of 12 months per year (October-September). To ensure that location of consumers is accurately recorded we drop those households whose average distance travelled to grocery stores identified in the consumer's shopping decisions changes by more than 10 km between the first and last quarter year of their appearance in the survey; this removes people who move house and whose new location is not updated. This yields 13,929 consumers from which we draw 2,000.

[20] We use the household income variable to allow price sensitivity to depend on demographics. The TNS data includes discrete demographic variables but not income. The UK's Expenditure and Food Survey (EFS) includes a variable for gross current household income (variable p352). We estimate household income by regressing the log of this income variable (for years 2003-2005) on other demographic variables in the ESF that map to those in the TNS survey, namely indicator variables for the number of cars $(0, 1, 2, \geq 3)$, adults $(1, \geq 2)$ children $(0, 1, 2, \geq 3)$, geographic region in Great Britain (10 regions), social class (6 classes as described in Appendix B), and whether the home is owned or rented. The R^2 is 0.59 and the number of observations in the regression is $17,699$.

set $c = \{j\}$. We write $n(c) \in \{1, 2\}$ to denote the number of stores in c. The consumer's set of available shopping choices $\mathcal{C}_i$ is thus all unordered pairs and singletons from $\mathcal{J}_i$. We suppress i subscripts, except on $\mathcal{J}_i$ and $\mathcal{C}_i$, until the discussion of consumer taste variation at the end of the section.

There are K demand categories $k \in \{1, ..., K\}$ at each store. For each category the consumer selects a single store $j \in c$.[21] These category-store choices are summarized in d, a K-vector that lists the store chosen for each category: e.g. if store j is chosen for the k'th category then the kth element of d is j. $\mathcal{D}_c$ is the set of possible alternatives for d given shopping choice c. (If c is a singleton, say $\{j\}$, there is only one option in $\mathcal{D}_c$, namely store j for each k). For each category the consumer makes a non-negative continuous quantity choice given by the $K \times 1$ vector $q \in \mathbb{R}^K_{\geq 0}$. Let p_{jk} be the price at store j of category k and let $p = (p_{jk})_{j \in \mathcal{J}_i,\, k \in \{1,...,K\}}$ be the vector of all store-category prices at stores in $\mathcal{J}_i$.

There are two sources of product differentiation. First, there is differentiation between stores at category level so that "store j for category k" and "store j' for category k" are viewed differently by any consumer. To model this let the consumer have a scalar store-category taste term μ_{jk} for each (j, k); we collect these in the full taste vector $\mu = (\mu_{jk})_{j \in \mathcal{J}_i,\, k \in \{1,...,K\}}$. The second source of differentiation is at shopping choice level c: the consumer has a scalar fixed cost Γ_c for each shopping choice c, which varies across c because of spatial variation; we collect these in the consumer's shopping cost vector $\Gamma = (\Gamma_c)_{c \in \mathcal{C}_i}$.

The consumer's net utility from shopping choice c, category-store allocation d, and quantity q, is given by the quasi-linear form

$$u(q, \mu_d) - \alpha p'_d q - \Gamma_c + \varepsilon_c \tag{1}$$

where μ_d and p_d are the "relevant" tastes and prices given category-store choice d—i.e. if d indicates store j is used for category k then the kth elements of μ_d and p_d are μ_{jk} and p_{jk} respectively. α is a price sensitivity scalar. The first two terms in (1) are variable utility, i.e. they depend on the quantity vector q. The last two terms are fixed utility associated with shopping choice c, where ε_c is the idiosyncratic utility associated with shopping choice c and is assumed to be drawn from a Type-1 Extreme Value distribution. Tastes (μ, α, Γ) vary in the population of consumers; we specify how in section 3.4.

3.2 A Simple Example: Two Stores and Unit Demands

To build intuition for the pricing incentives that are found in the general model we consider a simple version with two stores $\mathcal{J} = \{A, B\}$, three categories ($K = 3$), and unit demands

[21] The model can easily be generalized to allow the consumer to select two stores (each with a nonnegative quantity) for each category. This can be accommodated in the quadratic utility specification in section 3.3, where the number of continuous quantities in the utility function would be $2K$ instead of K when $n(c) = 2$, with second order parameters that govern inter-store intra-category substitution. This can also be accommodated in the econometric framework in Section 4. Given that category spending in the category's second store is low (see Section 2) we decided not to generalize in this way.

for all categories $q = \mathbf{1}$.[22] We also set $\varepsilon_c = 0$. Let tastes μ_{jk} be the consumer's gross utility from a unit of category k at store j. With these simplifications we have three shopping choices $\mathcal{C} = \{\{A\}, \{B\}, \{A, B\}\}$ and the store-category indicator d is a 3-vector of stores—e.g. $d = (A, B, A)$ indicates "store A for category 1, store B for category 2, and store A for category 3". There are eight possibilities for d, namely $\{(A, A, A), (A, A, B), ..., (B, B, B)\}$. Consumer i's choice problem is

$$\max_{c \in \mathcal{C}, d \in \mathcal{D}_c} \left[(\mu_d - \alpha p_d)' \mathbf{1} - \Gamma_c \right]. \tag{2}$$

The shoppers at store A can be decomposed into seven groups depending on which categories they allocate to store A. One group (the one-stop shoppers choosing $c = \{A\}$) allocates all the categories to A, i.e. $d = (A, A, A)$; the number of these shoppers $Q_{AAA}(p)$ is given by the number of consumers with values for (μ, α, Γ) that induce this choice. There are corresponding demand expressions for the six other groups of shoppers $(Q_{AAB}(p), ...)$ at store A, all of which are two-stop shoppers.

To consider the cross-category effect of a category-specific price change it is useful to write the profit of store A as the sum of contributions from each shopper group, i.e.

$$\begin{aligned} \pi_A &= Q_{AAA}(p)\left[p_{A1} + p_{A2} + p_{A3}\right] + Q_{AAB}(p)\left[p_{A1} + p_{A2}\right] + Q_{ABA}(p)\left[p_{A1} + p_{A3}\right] \\ &\quad + Q_{BAA}(p)\left[p_{A2} + p_{A3}\right] + Q_{ABB}(p)\left[p_{A1}\right] + Q_{BAB}(p)\left[p_{A2}\right] + Q_{BBA}(p)\left[p_{A3}\right] \end{aligned} \tag{3}$$

where we have normalized marginal costs to zero. Let there be an increase in p_{A1}. Consumers buying category 1 at store A can be divided into inframarginal shoppers (who do not respond to the price change) and those that are marginal. The marginal shoppers all respond on category 1—which generates an own-category effect—but vary in the extent of cross-category externalities depending on which shopper group they belong to in the decomposition in (3). We classify marginal shoppers into four exhaustive response classes depending on whether they are initially one- or two-stop shoppers and whether the price increase induces them to drop store A for all categories:

1. Initial one-stop shopper $c = \{A\}$ and $d = (A, A, A)$
   (a) Drop store A for all categories: d changes to (B, B, B).
   (b) Retain store A but drop it for at least category 1: d changes to (B, A, A), (B, B, A), or (B, A, B).
2. Initial two-stop shopper $c = \{A, B\}$ and $d \in \{(A, A, B), (A, B, B) \text{ or } (A, B, A)\}$.

[22] It is common in the multi-store multi-category theory literature, discussed in the introduction, to assume $J = 2$ and $K = 2$ and to define an individual consumer's tastes μ as a point in a unit square (e.g. consumers located in the top left of the square prefer firm A for the first product and frm B for the second, etc.). In this subsection we use $K = 3$ because one of the consumer responses below, namely (2b), is impossible with $K = 2$.

(a) Drop store A for all categories: d changes to (B, B, B).

(b) Retain store A but drop it for category 1: d changes to (B, A, B) or (B, B, A).

Of these four responses, (1a) has the maximal cross-category externality: each marginal consumer in this class transfers all three categories from the store with a total profit loss of $[p_{A1} + p_{A2} + p_{A3}]$. Response (2b) in contrast is limited to an own-category effect $[p_{A1}]$ for category 1 and has no cross-category profit externality. Response classes (1b) and (2a) are intermediate cases, with a cross-category externality for at most one category.

We can now relate the model to the two main questions we study in Section 6. First note that there are cross-category externalities, which have pro-competitive implications in supermarket organization, and that their magnitude depends on the distribution of consumers between response classes (1a-2b); they are greater the larger is the proportion of consumers in class (1a) relative to class (2b). Second, we can compare the pro-competitive effects of two groups of shoppers—one- and two-stop shoppers—by asking how much each group punishes the supermarket for the price increase. Conditional on being marginal (i.e. responding to the price change), one-stop shoppers tend to have larger cross-category externalities than two-stop shoppers. This does not, however, imply that one-stop shoppers penalize the firm more than two-stop shoppers, because a relatively low proportion of one-stop shoppers may be marginal. (A one-stop shopper, unlike a two-stop shopper, cannot switch category 1 between stores A and B without changing his shopping costs Γ_c, as he initially does not use both stores). Whether one-stop shoppers penalize the firm more than two-stop shoppers thus depends not just on the magnitude of the cross-category externalities per marginal shopper but also on the proportion of each type of shopper that is marginal.

3.3 Many Stores and Continuous Demands

We now return to the shopping choice framework in 3.1 which has many stores and continuous demands. Let the variable utility in (1) be given by the quadratic form[23]

$$u(\mu_d, q) - \alpha p_d' q = [\mu_d - \alpha p_d]' q - \frac{1}{2} q' \Lambda q \tag{4}$$

where Λ is a symmetric $K \times K$ matrix of second order quadratic terms, with elements $\Lambda_{kk'}$. We assume Λ does not vary across consumers.

First consider the consumer's category choices conditional on shopping choice c. We write these conditional-on-c choices with a c subscript: d_c (store chosen for each category) and q_c (quantity chosen for each category). A feature of the utility function as specified in (4) is that for any c the optimal choice of d is invariant in the level of q as the consumer

[23] Unlike many forms (e.g. AIDS), the quadratic is suitable for our purposes as it can accommodate zero demands at category level. It can also accommodate a variable number of stores depending on whether the consumer chooses to be a one-stop or two-stop shopper. Quadratic utility demand is used theoretically in Shaked and Sutton (1990) and estimated empirically in Wales and Woodland (1982).

always optimizes by selecting the store $j \in c$ with higher first order term for the category.[24] Thus we can solve the vector d_c of selected stores by category (without knowing q) as follows

$$d_c(p;\mu,\alpha) = [\arg\max_{j\in c}(\mu_{j1} - \alpha p_{j1}), ..., \arg\max_{j\in c}(\mu_{jK} - \alpha p_{jK})] \tag{5}$$

and $d_c(p;\mu,\alpha)$ is a function only of the parameters (μ,α) in the first order terms. The conditional-on-c category demands q_c are given by maximizing (4) at the relevant tastes and prices (μ_{d_c}, p_{d_c}) implied by $d_c(p;\mu,\alpha)$, subject to nonnegativity constraints, i.e.

$$q_c(p;\mu,\alpha,\Lambda) = \arg\max_{q\in\mathbb{R}^K_{\geq 0}} \left[\left[\mu_{d_c} - \alpha p_{d_c}\right]' q - \frac{1}{2} q'\Lambda q \right]. \tag{6}$$

This implies the following system of conditional category demands

$$q_{ck}(p;\mu,\alpha,\Lambda) = \max\left[\frac{1}{\Lambda_{kk}}\left(\left[\mu_{d_c} - \alpha p_{d_c}\right]_k - \sum_{k'\neq k}\Lambda_{kk'}q_{ck'}\right), 0\right] \text{ for } k = 1, ..., K \tag{7}$$

where $\left[\mu_{d_c} - \alpha p_{d_c}\right]_k$ is the kth row of the vector of relevant first order terms $\left[\mu_{d_c} - \alpha p_{d_c}\right]$. The diagonal second order quadratic terms, i.e. Λ_{kk} for any k, scale demand and allow own-price effects to vary across categories.[25] The off-diagonal second-order terms $\Lambda_{kk'}$ determine cross-category price effects (conditional on c). Combining (5) and (6) we obtain the conditional-on-c store-category demand functions:

$$q_{cjk}(p;\mu,\alpha,\Lambda) = q_{ck}(p;\mu,\alpha,\Lambda) \times 1[j = \arg\max_{j'\in c}(\mu_{j'k} - \alpha p_{j'k})] \quad \text{for } k = 1, ..., K. \tag{8}$$

Now consider how the consumer selects shopping choice c. We have seen that conditional on shopping choice c the consumer adjusts his category-specific choices d and q in response to the prices p and category-specific tastes μ that are relevant for c. The best utility a consumer with tastes (μ,α) facing prices p can achieve from shopping choice c is thus given by the indirect utility function

$$\begin{aligned} w_c(p;\mu,\alpha,\Lambda) &= \max_{d\in\mathcal{D}_c, q\in\mathbb{R}^K_{\geq 0}} \left[\left[\mu_d - \alpha p_d\right]' q - \frac{1}{2} q'\Lambda q \right] \\ &= \left[\mu_{d_c} - \alpha p_{d_c}\right]' q_c(p;\mu,\alpha,\Lambda) - \frac{1}{2} q_c(p;\mu,\alpha,\Lambda)'\Lambda q_c(p;\mu,\alpha,\Lambda) \end{aligned} \tag{9}$$

where the second line follows by substituting (5) and (6) into (4). The consumer selects the shopping choice c that gives the highest total utility net of shopping costs i.e.

$$\max_{c\in\mathcal{C}_i} \left[w_c(p;\mu,\alpha,\Lambda) - \Gamma_c + \varepsilon_c \right]. \tag{10}$$

[24] This follows by the absence of store-specific effects in the second order terms.

[25] The specification thus allows the conditional-on-c demand elasticity to vary across categories, as the slope and intercept both have a distinct parameter for each category.

The probability P_c the consumer chooses shopping choice c is given by[26]

$$P_c(p;\mu,\alpha,\Lambda,\Gamma) = \Pr(i \text{ chooses } c|\, p;\mu,\alpha,\Lambda,\Gamma) = \frac{\exp\left(w_c(p;\mu,\alpha,\Lambda)-\Gamma_c\right)}{\sum_{c'\in\mathcal{C}_i}\exp\left(w_{c'}(p;\mu,\alpha,\Lambda)-\Gamma_{c'}\right)}. \tag{11}$$

We now derive the model's prediction for the consumer's category demands at store j. There are a number of alternative shopping choices $c \in \{c|c \in \mathcal{C}_i, j \in c\}$ that the consumer could choose that include store j. Conditional on each of these alternatives for c we have an expression $q_{cjk}(\mu,\alpha,p)$ for the demand of the consumer, given in equation (8). The total expected demand at store j for category k for a consumer with tastes (μ,α,Γ) is thus given by aggregating over these shopping choice alternatives as follows

$$Q_{jk}(p;\mu,\alpha,\Lambda,\Gamma) \tag{12}$$

$$= \sum_{c\in\{c|c\in\mathcal{C}_i, j\in c\}} \left\{ q_{ck}(p;\mu,\alpha,\Lambda)\times 1[j=\arg\max_{j'\in c}(\mu_{j'k}-\alpha p_{j'k})]\times P_c(p;\mu,\alpha,\Lambda,\Gamma)\right\}$$

for $k = 1,..,K$. This is an "unconditional" demand in the sense that it does not condition on any shopping choice c. We adopt the notational convention of using upper case (Q) for demand that is unconditional in this sense and lower case (q) for demand conditional on c.

The right hand side of (12) decomposes three distinct responses that follow a change in price p_{jk}: (i) an "intensive margin" change in the consumer's continuous conditional demand q_{ck} holding store $j \in c$ and shopping choice c constant; (ii) a discrete change in the store $j \in c$ chosen for category k, holding shopping choice c constant; and (iii) a change in shopping choice c caused by the shopper either leaving store j altogether or retaining it but combining it with a different store. In the simple example in Section 3.2 two of these responses were present: (ii) and (iii); response (i) is now added because we allow for continuous demands.

3.4 Specification of Consumer Preferences

In this subsection we specify how preferences (μ,α,Γ) vary across consumers. To facilitate this we add subscripts: $(\mu_i,\alpha_i,\Gamma_i)$ for consumer i. We begin with consumer i's store-category taste scalar μ_{ijk} which is a function of observed and unobserved taste-shifters:

$$\mu_{ijk} = \xi_{fk}1_{[f(j)=f]} + \beta_{0k}\left(\beta_1 hz_i + \beta_2 sz_j + \beta_T T_i + \sigma_1\nu_i + \sigma_2\nu_{ik} + \sigma_3\nu_{ijk}\right). \tag{13}$$

[26] The scale of the parameters is determined by normalizing the parameter on the random shopping cost disturbance ε_c to unity so that it is a Type-1 Extreme Value draw. Note from (7) that conditional demands are homogeneous of degree zero in parameters (μ,α,Λ), i.e. $q_c(p;\kappa\mu^*,\kappa\alpha^*,\kappa\Lambda^*) = q_c(p;\mu^*,\alpha^*,\Lambda^*)$, where $(\mu^*,\alpha^*,\Lambda^*)$ represents some arbitrary value. This does not however allow another normalization because variable utility (9) is homogeneous of degree one in the same parameters, i.e. $w_c(p;\kappa\mu^*,\kappa\alpha^*,\kappa\Lambda^*) = \kappa w_c(p;\mu^*,\alpha^*,\Lambda^*)$, so that their scale κ determines the relative importance of variable utility and shopping costs in the consumer shopping choice problem (10). Since we have not normalized (μ,α,Λ) we do not need a further parameter to multiply w_c in (10).

The first term ξ_{fk} is the mean utility associated with firm f and category k. ξ_{fk} may vary by firm because different firms do not offer the same branded products, and because many products (e.g. "private labels") are firm-specific. Variation in firm-category strengths was suggested by the data presented in Section 2.[27]

The remainder of μ_{ijk}, i.e. $\beta_{0k}(\beta_1 hz_i + ...)$, allows the utility for consumer i and store j to deviate from the firm-category mean. In the interests of parsimony the parameters (but not the random terms) in this component are common across categories, up to a scaling term β_{0k} which allows the size of the effect to vary across categories (to normalize we set $\beta_{0k} = 1$ for $k = 1$). The observable household and store variables are household size hz_i which allows continuous demand to be increasing in household size, the log of the store's floor space sz_j which allows larger stores to have a better selection of products, and quarter and year dummies T_i. The remaining terms in (13) are three random taste components (each iid $N(0,1)$): a general effect ν_i, a category-specific effect ν_{ik}, and a store-category effect ν_{ijk}. The last of these introduces (horizontal) product differentiation at store-category level, allowing each consumer to view stores differently for any category.[28] Thus category-store differentiation is partly vertical, reflecting differences in the average quality of stores for any category, and partly horizontal, reflecting variation in individual consumer preferences.

The price coefficient α_i is specified to allow heterogeneity in price sensitivity

$$\alpha_i(\alpha, \nu_i^\alpha) = (\alpha_1 + \alpha_2 / y_i)\, \nu_i^\alpha \tag{14}$$

where y_i is household i's income per capita and ν_i^α is a Rayleigh(1) random variable. This distribution is convenient as it ensures positive price sensitivity $\alpha_i > 0$ for all i, as long as α_1 and α_2 are positive.

Finally, shopping costs are given by

$$\Gamma_{ic} = \left(\gamma_{11} + \gamma_{12}\nu_{i1}^\Gamma\right) 1_{[n(c)=2]} + \left(\gamma_{21} + \gamma_{22}\nu_{i2}^\Gamma\right) dist_{ic} \tag{15}$$

where $n(c)$ is the number of stores in c and $dist_{ic} = \sum_{j \in c} dist_{ij}$ is the sum of the distances from the consumer to the stores. ν_{i1}^Γ and ν_{i2}^Γ are each iid $N(0,1)$.[29]

[27] The main firms are listed in Table 3 in Section 2. To economize on ξ parameters we aggregate two groups of smaller firms: the "Discounters" (Aldi, Lidl, Netto), which have a similar quality position across categories, and the Others, which are smaller chains (namely Co-op, Somerfield, and a group of very minor chains). This results in 9 firms (or firm groups) that have a distinct ξ for each k: ASDA, Morrison, Sainsbury, Tesco, M&S, Waitrose, Iceland, Discounters, and Others.

[28] As the notation implies, i has the same realization of ν_{ijk} for store j for all shopping choices c for which $j \in c$, so there is correlation in unobserved utility between shopping choices c sharing common stores.

[29] We assume that shoppers choose stores on a weekly basis (regardless of trip frequency); see the discussion in Section 2. The inclusion of heterogeneity in shopping costs allows shoppers that vary in frequency of shopping to have different costs at weekly level for any given shopping choice.

4 Estimation

The parameters to be estimated are in two groups: those in variable utility, which we collect as $\theta = (\alpha, \beta, \xi, \sigma, \Lambda)$, and those in shopping costs γ. Only the first parameter group θ enters the consumer's conditional-on-c category-store demand functions (8) which can be written

$$q_{icjk} = q_{cjk}(\theta; x_{ic}^{w}, \nu_{ic}^{w}) \quad \text{for } k = 1, .., K, \tag{16}$$

where x_{ic}^{w} denotes the observables (including prices) of consumer i and stores $j \in c$ entering variable utility, and $\nu_{ic}^{w} = (\nu_i, \nu_{ik}, \nu_{ijk}, \nu_i^{\alpha})_{j \in c, k=1,..,K}$ denotes unobservable taste effects entering variable utility. The probability (11) that consumer i chooses shopping choice $c \in \mathcal{C}_i$ is a function of both groups of parameters, written

$$P_c(\theta, \gamma; x_i^{w}, x_i^{\Gamma}, \nu_i^{w}, \nu_i^{\Gamma}) \tag{17}$$

where $(x_i^{w}, \nu_i^{w}) = (x_{ic}^{w}, \nu_{ic}^{w})_{c \in \mathcal{C}_i}$, as defined above, and $\left(x_i^{\Gamma}, \nu_i^{\Gamma}\right) = (x_{ic}^{\Gamma}, \nu_{ic}^{\Gamma})_{c \in \mathcal{C}_i}$ denote observables (including prices) and random tastes entering shopping costs.

We could proceed by estimating the parameters in two steps: first conditioning on shopping choice c to estimate θ using the conditional demand system (16), which is linear in x_{ic}^{w} when the nonnegativity constraints do not bind. In the second step we could then estimate γ using shopping choice probabilities (17) and the first-step estimate of θ. There are two problems with this approach. First, since we observe zero demands at the category-store level, the nonnegativity constraints in (6) bind with a positive probability. In the presence of corner solution outcomes, the marginal effects of x_{ic}^{w} on expected demand are not consistently estimated unless the nonnegativity constraints are modelled explicitly (see Amemiya (1974)). The second problem is that consumers are not randomly assigned to shopping choices c, as they self-select based on taste draws $(\nu_i^{w}, \nu_i^{\Gamma})$ which are not observed by the econometrician. This results in a selection problem in which a consumer's shopping choice c—and hence its observed characteristics x_{ic}^{w}—depend on ν_{ic}^{w}. This implies that the mean independence condition $E(\nu_{ic}^{w} | x_{ic}^{w}) = 0$ does not hold (see Heckman (1979) and Dubin and McFadden (1984)).

To deal with these issues we estimate the model in one step, using predictions which fully specify both the consumer's nonnegativity constraints and shopping choice c. We use three unconditional predictions. The first is the expected demand for category $k = 1, .., K$ in store j and shopping choice c

$$Q_{cjk}(\theta, \gamma; x_i^{w}, x_i^{\Gamma}) = \int \left\{ q_{cjk}(\theta; x_{ic}^{w}, \nu_{ic}^{w}) \times P_c(\theta, \gamma; x_i^{w}, x_i^{\Gamma}, \nu^{w}, \nu^{\Gamma}) \right\} dF(\nu^{w}, \nu^{\Gamma}) \tag{18}$$

where the integrand is the conditional-on-c demand function (16) for category k at store j multiplied by the probability (17) of choosing c. The second prediction is the joint probability of observing that the consumer selects shopping choice c and buys category k at store

$j \in c$, written

$$D_{cjk}(\theta,\gamma;x_i^w,x_i^\Gamma) = \int \left\{1\left[q_{cjk}(\theta;x_{ic}^w,\nu_{ic}^w)>0\right] \times P_c(\theta,\gamma;x_i^w,x_i^\Gamma,\nu^w,\nu^\Gamma)\right\} dF(\nu^w,\nu^\Gamma). \quad (19)$$

The integrand is an indicator function for positive demand for k at store j conditional on shopping choice c multiplied by the probability of choosing c. The third is the probability a consumer selects shopping choice c

$$P_c(\theta,\gamma;x_i^w,x_i^\Gamma) = \int P_c(\theta,\gamma;x_i^w,x_i^\Gamma,\nu^w,\nu^\Gamma) dF(\nu^w,\nu^\Gamma).$$

In all three predictions we integrate over the multivariate distribution of unobservable consumer tastes $F(\nu^w,\nu^\Gamma)$ specified in Section 3.4.

For each consumer we observe the choices $[(Q_{icjk},D_{icjk},)_{j\in c,k=1,..,K},P_{ic}]_{c\in\mathcal{C}_i}$ that correspond to these predictions, where $Q_{icjk}\geq 0$ is a continuous nonnegative quantity observation and $D_{icjk}\in\{0,1\}$ and $P_{ic}\in\{0,1\}$ are discrete indicator variables.[30] To estimate the parameters we assume the prediction errors are mean independent of instruments $[(Z_{icjk}^Q,Z_{icjk}^D)_{j\in c,k=1,..,K},Z_{ic}^P]_{c\in\mathcal{C}_i}$, where each Z is a (row) vector of exogenous data relevant to the consumer's decisions. This gives the following moment conditions

$$\begin{aligned} E\left[Q_{icjk}-Q_{cjk}(\theta,\gamma;x_i^w,x_i^\Gamma) \mid Z_{icjk}^Q\right] &= 0 \text{ for } k=1,..,K \quad (20)\\ E\left[D_{icjk}-D_{cjk}(\theta,\gamma;x_i^w,x_i^\Gamma) \mid Z_{icjk}^D\right] &= 0 \text{ for } k=1,..,K \quad (21)\\ E\left[P_{ic}-P_c(\theta,\gamma;x_i^w,x_i^\Gamma) \mid Z_{ic}^P\right] &= 0. \quad (22)\end{aligned}$$

The condition (20) implies a moment equation for each of the instruments in the vector Z_{icjk}^Q for $k=1,...,K$. The conditions (21) and (22) imply corresponding moment equations.

The instruments used in these conditions are the non-price observables that enter the consumer's joint discrete-continuous utility problem, plus an instrument for price. They include characteristics at the level of the household i, the store $j\in c$, and the shopping choice c, that appear in either the conditional category demand system (16) or the shopping choice probabilities (17). To allow for the possibility that price is correlated with unobserved temporal demand shocks we use a price instrument given by the fitted value from a series of category-specific regressions of prices on cost-shifting variables that we assume are not related to unobserved grocery demand shocks—namely category-specific input prices that are traded on world markets, category-specific retail prices in a neighboring country (Ireland), and the £/Euro exchange rate—as well as the firm and time dummies used in the model.[31]

[30] For each category j is observed to be chosen for k if it is the store with positive (or largest) expenditure for the category. The consumer's observed shopping choice c consists of these chosen stores, indicated by $P_{ic}\in\{0,1\}$. $D_{icjk}\in\{0,1\}$ indicates if $j\in c$ is chosen for k and c is the consumer's observed shopping choice, while Q_{icjk} is the quantity of k in j if j is chosen for k and c is i's observed shopping choice.

[31] The use of a fitted value for the price instrument avoids introducing a large number of extra instruments and moment conditions. We do eight separate reduced form price regressions (one for each category) where the dependent variable is the category price. There are 21,216 week-firm-demographic group observations

The instruments for each moment condition are as follows. Z^Q_{icjk} is the 1×21 vector comprising household size hz_i, household income y_i, year dummies for two of the three October-September annual periods, three quarter dummies, store floorspace sz_j, nine dummies $1_{[f(j)=f]}$ for firms f that have a specific firm-category effect ξ_{fk} (specified in footnote 27), the price instrument for category k, the ratio of the price instrument to per-capita income, total distance $\sum_{j\in c} dist_{ij}$ to shopping choice c, and a dummy for two stores $1_{[n(c)=2]}$ in shopping choice c. (As the firm dummies sum to unity by construction a constant term is redundant). Z^D_{icjk} is the 1×16 vector comprising the instruments in Z^Q_{icjk} excluding the five time dummies, which are less important for discrete than for continuous choices. Finally Z^P_{ic} is a 1×3 vector of variables relating to shopping costs, namely total distance $\sum_{j\in c} dist_{ij}$, total distance squared, and a dummy for two-stop shopping $1_{[n(c)=2]}$.

Given a sample of N independent observations of consumers $i = 1, ..., N$ we replace the population orthogonality conditions implied by (20-22) with the analogous conditions for the empirical moments $g(\theta, \gamma) = N^{-1} \sum_{i=1}^N g_i(\theta, \gamma)$, where $g_i(\theta, \gamma)$ is consumer i's moment contribution, given by

$$g_i(\theta,\gamma) = \begin{bmatrix} \sum_{c\in\mathcal{C}_i} \sum_{j\in c} Z^{Q\,\prime}_{icj1} \left[Q_{icj1} - Q_{cj1}(\theta,\gamma; x_i^w, x_i^\Gamma)\right] \\ \cdots \\ \sum_{c\in\mathcal{C}_i} \sum_{j\in c} Z^{Q\,\prime}_{icjK} \left[Q_{icjK} - Q_{cjK}(\theta,\gamma; x_i^w, x_i^\Gamma)\right] \\ \sum_{c\in\mathcal{C}_i} \sum_{j\in c} Z^{D\,\prime}_{icj1} \left[D_{icj1} - D_{cj1}(\theta,\gamma; x_i^w, x_i^\Gamma)\right] \\ \cdots \\ \sum_{c\in\mathcal{C}_i} \sum_{j\in c} Z^{D\,\prime}_{icjK} \left[D_{icjK} - D_{cjK}(\theta,\gamma; x_i^w, x_i^\Gamma)\right] \\ \sum_{c\in\mathcal{C}_i} Z^{P\prime}_{ic} [P_{ic} - P_c(\theta,\gamma; x_i^w, x_i^\Gamma)] \end{bmatrix}. \tag{23}$$

To estimate the parameters we use the GMM estimator

$$(\hat{\theta}, \hat{\gamma}) = \arg\max_{\theta,\gamma} \left[\breve{g}(\theta,\gamma)' W^{-1} \breve{g}(\theta,\gamma)\right] \tag{24}$$

where $\breve{g}(\theta, \gamma)$ denotes moments that are calculated using a fixed number of draws for unobserved tastes (ν_i^w, ν_i^Γ) and $W = N^{-1} \sum_{i=1}^N \breve{g}_i(\theta,\gamma)\breve{g}_i(\theta,\gamma)'$ is the covariance matrix of the simulated contributions $\breve{g}_i(\theta, \gamma)$, evaluated at a first-stage estimate of (θ, γ).[32] The estimator is consistent for a fixed number of simulation draws because the simulated predictions enter the moment conditions linearly (see McFadden (1989) and Pakes and Pollard (1989)). We use 2000 simulation draws (one for each household) for $\breve{g}_i$ in estimation and in the standard

for price in each category as detailed in footnote 18. The category-specific input prices (and retail prices in Ireland) used as exogenous variables are detailed in Appendix C. The R-squared of the eight cateory price regressions are {0.98,0.96,0.95,0.98,0.97,0.95,0.96,0.89}, and the F-statistics for the excluded regressors (i.e. those that do not appear as observable data in the utility model) are {57.41, 62.36, 4.97, 15.71, 127.8, 11.84, 12.69, 375.61), arranging categories alphabetically.

[32] The first stage uses a block-diagonal weighting matrix with blocks $\{N^{-1} \sum_{i,c,j} Z^{Q\,\prime}_{icjk} Z^Q_{icjk}\}^{-1}$, $k = 1, \ldots, K$, for moment conditions (20), $\{N^{-1} \sum_{i,c,j} Z^{D\,\prime}_{icjk} Z^D_{icjk}\}^{-1}$, $k = 1, \ldots, K$, for moment conditions (21) and $\{N^{-1} \sum_{i,c} Z^{P\prime}_{ic} Z^P_{ic}\}^{-1}$ for moment conditions (22).

errors. Standard errors are adjusted for simulation noise.[33]

The identification of parameters is facilitated by two features of the model. The first is that we have prediction errors for observations at the three distinct levels of consumer response decomposed in equation (12): continuous store-category demand Q_{icjk}, discrete store-category indicators of positive demand D_{icjk}, and discrete shopping choice indicators P_{ic}. Each of these choices is affected by the full set of parameters (θ, γ) that enter net utility, and each adds information about consumer preferences. The second feature that helps identification is the richness of choice set variation across consumers. We illustrated this in Table 2 in Section 2. The variation stems from the fact that each consumer i has a unique location and a different set of stores within any given distance. Thus the set of alternative shopping choices $\mathcal{C}_i$ is unique to each consumer and the instruments that are derived from this choice set $[(Z^Q_{icjk}, Z^D_{icjk})_{j\in c,k=1,..,K}, Z^P_{ic}]_{c\in\mathcal{C}_i}$ are different for each consumer.

5 Estimates and Model Fit

In this section we present the parameter estimates and discuss the fit of the estimated model. We estimate two specifications. As a simple starting point Model 1 assumes independence between product categories in terms of variable utility, so that we set to zero the cross-category second order terms $\Lambda_{kk'}$ in quadratic utility (4), and the scaling term σ_1 on cross-category taste shocks. Model 2 generalizes by relaxing these assumptions.

Panel A of Table 4 shows the estimated parameters in the store-category taste effects μ_{ijk}, which enter the first order term in quadratic utility, as specified in equation (13). The parameters (β_1, β_2) have intuitive signs, as the effect of household and store size are both positive. σ_1 is only estimated for Model 2 and is small and insignificant, which suggests that cross-category taste correlation is already captured in the model through other household-specific variation in the model, e.g. household size variation in μ_{ijk} or the variation in the price coefficient α_i. The estimates for σ_2, which scales unobserved variation in category-specific tastes, and σ_3, which scales unobserved category-store tastes, are both significant. Models 1 and 2 both include firm-category fixed effects ξ_{fk} and below we consider their implications for the fit of the model.

Panel B reports the parameters in the matrix Λ of second order terms in quadratic utility. In estimation we separate this matrix into two components $\Lambda = \Phi'\Omega\Phi$ where Φ is

[33] The standard asymptotic covariance matrix of the (second-stage) estimates $(\hat\theta, \hat\gamma)$ is given by $N^{-1}\left(\nabla\breve{g}(\hat\theta,\hat\gamma)\ W(\hat\theta,\hat\gamma)^{-1}\ \nabla\breve{g}(\hat\theta,\hat\gamma)'\right)^{-1}$. We correct for simulation noise by instead using

$$N^{-1}\left(\nabla\breve{g}(\hat\theta,\hat\gamma)\ [W(\hat\theta,\hat\gamma)+S(\hat\theta,\hat\gamma)]^{-1}\ \nabla\breve{g}(\hat\theta,\hat\gamma)'\right)^{-1},$$

where $S(\hat\theta,\hat\gamma) = N^{-1}\sum_{i=1}^{N}\left(\breve{g}_i(\hat\theta,\hat\gamma) - E_r[\breve{g}_i(\hat\theta,\hat\gamma)]\right)\left(\breve{g}_i(\hat\theta,\hat\gamma) - E_r[\breve{g}_i(\hat\mu,\hat\gamma)]\right)'$ is the variance of the simulation noise (see Stern (1997), equation (3.18), p2029), $\breve{g}_i$ is computed as in (23), $E_r[\breve{g}_i]$ is the same quantity as the number of simulation draws gets large (we use 3000 draws for each household), and $(\hat\theta, \hat\gamma)$ are (second stage) estimates.

Table 4: Estimated Parameters

		Model 1		Model 2	
		Estimate	Std. Error	Estimate	Std. Error
A: Store-Category Taste Effects					
Bakery	β_{01}	2.776	0.491	2.688	0.384
Dairy	β_{02}	1.518	0.285	1.503	0.343
Drink	β_{03}	1.489	0.018	1.530	0.026
Dry Grocery	β_{04}	2.988	0.695	2.688	0.545
Fruit & vegetable	β_{05}	3.730	0.830	3.570	0.705
Household goods	β_{06}	1.339	0.336	1.358	0.178
Meat	β_{07}	2.392	0.430	2.348	0.075
ln(floor space)	β_1	0.057	0.005	0.058	0.001
Household size	β_2	0.058	0.010	0.059	0.007
Year & Quarter effects		Yes		Yes	
Scale of Taste Draws (ν):					
Overall	σ_1	–	–	0.003	0.006
Category	σ_2	0.117	0.008	0.114	0.002
Store-category	σ_3	0.178	0.027	0.188	0.004
Firm-Category effects	ξ_{fk}	Yes		Yes	
B: Second-Order Quadratic Parameters					
Bakery	Φ_{11}	0.587	0.053	0.579	0.047
Dairy	Φ_{22}	0.400	0.047	0.400	0.084
Drink	Φ_{33}	0.254	0.021	0.263	0.016
Dry Grocery	Φ_{44}	0.502	0.071	0.469	0.064
Fruit & vegetable	Φ_{55}	0.506	0.068	0.497	0.071
Household goods	Φ_{66}	0.254	0.049	0.260	0.024
Meat	Φ_{77}	0.327	0.039	0.327	0.020
Milk	Φ_{88}	0.462	0.038	0.467	0.128
Meat - Fruit & veg.	Ω_{57}	–	–	0.006	0.111
Bakery - Milk	Ω_{18}	–	–	0.004	0.182
Dairy - Drink	Ω_{23}	–	–	0.008	0.128
C: Price Parameters					
Constant	α_1	0.250	0.041	0.255	0.004
Income Per Capita	α_2	15.845	3.567	15.677	0.316
D: Shopping Costs					
Shopping Cost	γ_{11}	14.683	4.883	17.436	9.711
Standard Deviation	γ_{12}	25.862	10.257	31.409	19.153
Distance Cost	γ_{21}	1.477	0.249	1.456	0.195
Standard Deviation	γ_{22}	1.307	0.283	1.332	0.249
Objective Function		0.291		0.286	

Notes: Parameters are estimated by GMM. Standard errors are corrected for simulation noise as detailed in Section 4.

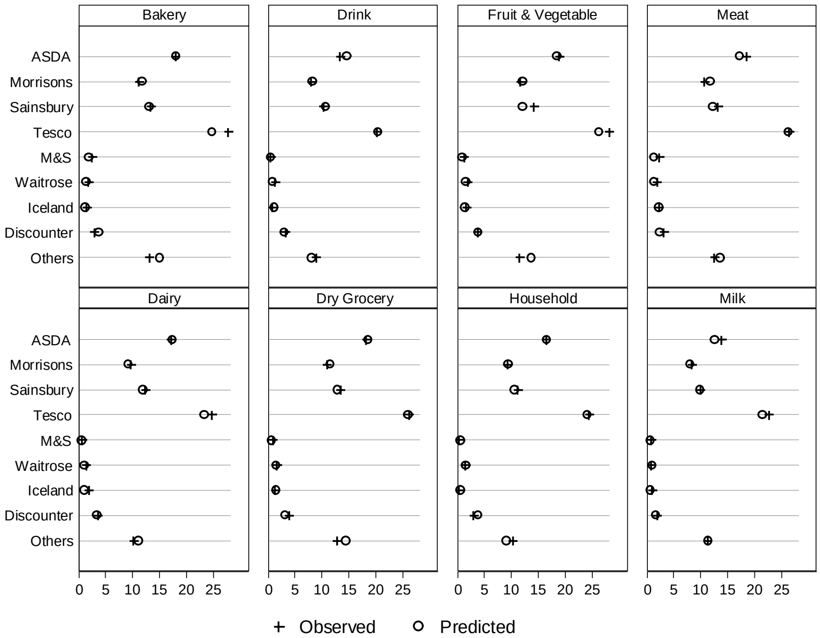

Figure 1: Predicted and Observed Category-Firm Discrete Market Shares. The predictions (and observations) are for the 2000 consumers sample used to estimate the model (using the same taste draws as in estimation). The horizontal axis is the market share (expressed as a percentage) in terms of number of consumers that choose each firm for each category, i.e. s_{fk}^{D} as defined in the text.

a diagonal $K \times K$ matrix (with zeros on the off-diagonals) and Ω is a symmetric $K \times K$ matrix with the elements on the main diagonal fixed to unity. This decomposition helps with interpretation as the off-diagonals $\Omega_{kk'}$ are a units-free measure the extent to which categories are independent in utility: a value of zero implies that categories k and k' are independent, while a value of one implies perfect substitutes. The category-slope terms $\Phi_{11}, ..., \Phi_{88}$ are all significant and vary across categories (note that $\Phi_{kk} = \sqrt{\Lambda_{kk}}$). The off-diagonal parameters $\Omega_{kk'}$ (estimated for Model 2) are positive, which implies that marginal utility for category k declines as the quantity $q_{k'}$ of category $k' \neq k$ increases, but the estimated parameters are small and insignificant. In the interest of parsimony we estimate only a few of these parameters.

The parameters in the price sensitivity term (14) are reported in Panel C. These are of the expected signs: α_1 is positive so that consumers prefer lower prices and α_2 is positive so that price sensitivity decreases as per-capita household income increases. Finally, Panel D reports the parameters γ that enter the consumer's shopping costs Γ_{ic}. The parameter signs imply that both distance and the number of stores used increase shopping costs. The mean effects of both variables are significant and the spread parameter is significant for the distance parameter.

The estimated model generates choice outcomes at three levels: continuous and discrete demands at store-category level and a discrete choice of store(s) at the shopping choice level. In the rest of this section we check the fit of the model to ensure it is flexible enough to match all these choice predictions accurately. For example firm parameters appear only

Table 5: In-Sample and Out-of-Sample Fit: Firm-Category and Firm-Level Choices

A: Firm-Category Demand	Shoppers D			Quantities Q		
(Model, In- or Out-of-Sample):	(1, In)	(2, In)	(2, Out)	(1, In)	(2, In)	(2, Out)
Absolute pred. error (for s^D_{fk}, s^Q_{fk})	0.007	0.006	0.008	0.013	0.013	0.018
Correlation ρ(Pred, Obs)						
All Shoppers	0.993	0.990	0.983	0.985	0.987	0.983
One Stop Shoppers	0.991	0.979	0.977	0.989	0.989	0.977
Two Stop Shoppers	0.978	0.962	0.958	0.965	0.965	0.958

B: Firm-Level Demand (Model 2, In-Sample)	Market shares of Firms				Consumers by Firm (Means)			
	Revenues		Shoppers		One-stop (1/0)		Household size	
	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs
ASDA	0.202	0.216	0.170	0.176	0.64	0.63	4.63	4.70
Morrisons	0.133	0.132	0.131	0.129	0.61	0.55	4.67	4.37
Sainsbury	0.160	0.171	0.126	0.141	0.61	0.59	4.65	5.17
Tesco	0.308	0.319	0.255	0.271	0.63	0.62	4.75	4.80
M&S	0.021	0.014	0.017	0.029	0.21	0.26	3.48	3.92
Waitrose	0.021	0.022	0.017	0.019	0.47	0.50	4.68	4.88
Iceland	0.014	0.013	0.029	0.027	0.32	0.30	3.96	3.63
Discounter	0.025	0.025	0.050	0.048	0.41	0.29	3.88	3.99
Other	0.116	0.089	0.191	0.159	0.49	0.47	4.56	4.33

Notes: Panel A: Statistics are for the 72 category-firm predictions. Prediction errors, reported as averages, are for market shares in terms of shoppers D and quantities Q as defined in text. Correlation coefficients are for number of shoppers D and quantities Q. In-sample predictions use the 2000 consumer taste draws used in estimation. Out-of-sample statistics use a new sample of 3000 consumers and new taste draws. Panel B: market shares in terms of consumers adjusted for two-stop shopping so they add to 1.

in variable utility (entering as category-firm effects ξ_{fk}) and they serve the dual purpose of fitting (continuous and discrete) category demands for each firm, and discrete shopping choices that include stores of each firm, so it is informative to check whether the model fits the data at these different levels. Along with the in-sample fit, we consider the out-of-sample fit to provide an external check on the model. The out-of-sample predictions are generated by applying the estimated parameters to 3000 new randomly-drawn consumers that were not in the original sample used for estimation and a fresh set of random taste draws.

We begin by considering how well the model predicts demand at a firm-category level. A useful discrete demand prediction of the model is the total number of consumers that buy category k from firm f, which we call the number of "shoppers", i.e.

$$D_{fk}(p) = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j \in \mathcal{J}_f} \sum\nolimits_{c \in \{c | c \in \mathcal{C}_i, j \in c\}} D_{cjk}(\hat{\theta}, \hat{\gamma}; x_i^w, x_i^\Gamma) \tag{25}$$

where $D_{cjk}(\hat{\theta}, \hat{\gamma}; x_i^w, x_i^\Gamma)$ is the probability consumer i buys a positive quantity of k in store j in shopping choice c, defined in (19), and the innermost sum is over shopping choices c

Table 6: Observed and Predicted Shopping Choices by Firm

		ASDA	Morr	Sains	Tesco	M&S	Wait	Icel	Disc	Other
ASDA	Pred	281.9	25.5	21.9	39.9	4.8	2.9	7.8	12.6	42.0
	Obs	287	36	19	42	6	2	11	20	32
Morrisons	Pred		211.0	11.2	28.4	5.4	1.8	5.2	9.9	37.8
	Obs		184	19	44	6	1	6	14	23
Sainsbury	Pred			197.5	41.2	6.8	4.1	5.5	9.5	28.6
	Obs			216	51	11	6	4	9	29
Tesco	Pred				416.2	11.6	7.4	17.9	20.6	75.5
	Obs				436	21	8	16	22	60
M&S	Pred					9.4	0.4	1.2	1.6	4.0
	Obs					20	4	0	1	7
Waitrose	Pred						21.4	1.1	1.9	4.1
	Obs						25	1	0	3
Iceland	Pred							24.4	3.1	9.2
	Obs							21	4	8
Discounters	Pred								54.4	13.2
	Obs								37	16
Other	Pred									258.1
	Obs									212

Notes: Predicted and observed number of consumers selecting each firm combination. The diagonal shows the number using one firm only. Predictions and observations are for the 2000 households (and taste draws) used in estimation.

that include store j. $\mathcal{J}_f$ is the set of stores owned by firm f. Firm f's share of category k in terms of shoppers is then $s^D_{fk} = D_{fk}(p)/\sum_{f'} D_{f'k}(p)$. Figure 1 shows a close match between the predicted and observed s^D_{fk} for each firm and category, using Model 2 and the sample used to estimate the model.

The continuous prediction of the model at the same level is the total quantity of category k sold by the firm, i.e.

$$Q_{fk}(p) = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j\in\mathcal{J}_f} \sum\nolimits_{c\in\{c|c\in\mathcal{C}_i, j\in c\}} Q_{cjk}(\hat{\theta}, \hat{\gamma}; x^w_i, x^\Gamma_i) \tag{26}$$

where $Q_{cjk}(\hat{\theta}, \hat{\gamma}; x^w_i, x^\Gamma_i)$ is i's category demand at store j in shopping choice c defined in (18). The firm's category-specific market share in terms of quantities is $s^Q_{fk} = Q_{fk}(p)/\sum_{f'} Q_{f'k}(p)$.

Panel A of Table 5 considers the fit for the discrete and the continuous measures of firm-category demand. The first row presents the mean absolute prediction error for market shares s^D_{fk} and s^Q_{fk}. The discrete market shares s^D_{fk} have a mean absolute error of 0.006 to 0.008—i.e. s^D_{fk} is predicted on average to be within one percentage point of its observed value. This level of accuracy is similar for both in-sample predictions and the out-of-sample predictions. The quantity market shares s^Q_{fk} have a mean absolute error of 0.013 to 0.018 so that the level of accuracy is within two percentage points, even for the out-of-sample predictions. Correlation coefficients measuring the relationship between predicted and observed

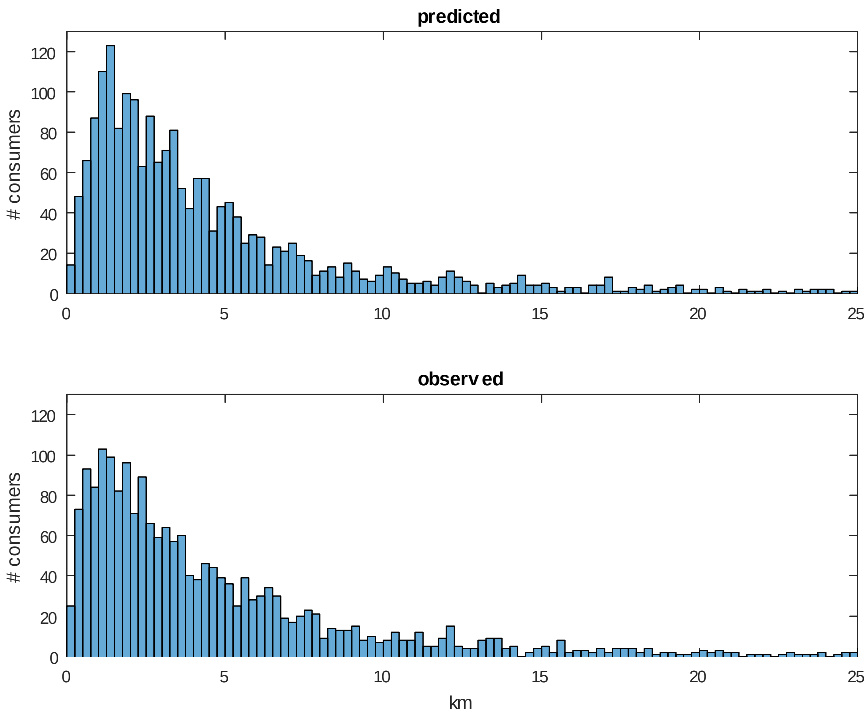

Figure 2: Histograms of predicted and observed distances. The predictions are generated using Model 2 and the 2000 consumers in the estimation sample with the same taste draws used in estimation.

demands D_{fk} and Q_{fk} are given in the next row and indicate a high level of fit both for in-sample and out-of-sample predictions at firm-category level. The last two rows check the fit separately for demand from two different shopper groups: one- and two-stop shoppers. Overall we find that Model 2 fits the data at least as well as Model 1, and we consider only Model 2 hereafter.

Panel B of Table 5 considers the fit at shopping choice level for the main firms in the market. This allows us to check that the model predicts the market share and shopper mix accurately for each firm. The model accurately predicts the market shares of the firms—both in terms of revenues and in terms of number of shoppers. The next two columns ("One-stop") show that the model does a good job of predicting the number of one-stop shoppers by firm; in particular the fact that shoppers using Big Four firms are more likely to be one-stop shoppers. The final columns show the average household size of consumers choosing each firm. The model replicates the observed pattern in which firms operating small floorspace stores (e.g. Discounters and M&S) attract customers with a smaller household size.

We now check how well the model predicts some other aspects of the shopping choices c. Table 6 looks at the in-sample fit for the frequency of each possible combination of firms. Note that there is no direct parameter to capture this (like a "firm pair" dummy), so it is interesting to see whether the model fits this aspect of the data well. The diagonal gives the consumers that shop only at one firm and the upper triangle gives the numbers that combine each pair of firms, e.g. the number that use only ASDA are 287 (observed) and 281.9 (predicted) respectively, and the numbers that combine ASDA and Tesco are 42 (observed) and 39.9 (predicted).

Finally we provide a visual check of the spatial fit of the model. Figure 2 presents histograms of observed and predicted travel distances to consumers' chosen stores for the 2000 shoppers in the data. The histograms indicate that most shoppers travel less than 5km and relatively few travel more than 10km from their home. As well as being consistent with the observed data, these predictions are consistent with external survey evidence from CC (2000, 4.129), which found 91% of shoppers had a travel time of 20 minutes or less to their supermarket—a distance of about 10-15km at standard driving speeds of 30-45km/hour.

6 Analysis of Supermarket Pricing

6.1 Supermarket Organization and Equilibrium Profit Margins

We now use the estimated model to analyze supermarket pricing. In 6.2 we report the own- and cross-category demand effects implied by the estimated parameters, and in 6.3 we solve for the Nash equilibrium profit margins implied by the model, and compare them with external data on profit margins as a validity check. We then consider the two main policy-relevant questions of interest: we measure cross-category externalities and assess their impact on market power, and we compare the pro-competitive impacts of one-stop and two-stop shoppers.

We compare two forms of organization. In supermarket organization the firm sets prices to internalize external effects on all other categories, while in the alternative of independent category sellers the price maximizes category k profit only; nesting these we have the pricing problem

$$\max_{p_{fk}} \left\{ Q_{fk}(p)\left[p_{fk} - mc_{fk}\right] + \chi_f \sum\nolimits_{k'=k} Q_{fk'}(p)\left[p_{fk'} - mc_{fk'}\right] \right\} \tag{27}$$

where $\chi_f \in \{0,1\}$ is 1 for supermarket pricing and 0 for independent category sellers, and where p_{fk} is the national price and mc_{fk} the marginal cost for firm f and category k. We assume Nash equilibrium prices which implies the following set of first order conditions[34]

$$\underbrace{Q_{fk}\left(\frac{\partial Q_{fk}}{\partial p_{fk}}\right)^{-1} + p_{fk}}_{\text{marginal category revenue } (mr_{fk})} + \underbrace{\chi_f \sum\nolimits_{k' \neq k} \left\{ \frac{\frac{\partial Q_{fk'}}{\partial p_{fk}}}{\frac{\partial Q_{fk}}{\partial p_{fk}}} \left[p_{fk'} - mc_{fk'}\right] \right\}}_{\text{marginal externality } (me_{fk})} = mc_{fk}. \tag{28}$$

This condition states that the marginal benefit of inducing an extra unit of demand for

[34] As noted in Section 2 the price indices for any (f,k) differ across demographic groups to reflect different consumption weights for products within the category. The derivative of Q_{fk} with respect to the price of (f',k') is the effect on Q_{fk} of the marginal increase to each demographic type's price index implied by an equal marginal increase to the prices of each of the individual products in the category.To see that this leads to an equal marginal change in each consumer's price index, consider a simple example with two prices p_1,p_2 and two demographic groups a and b with weights $w_{a1} + w_{a2} = 1$ and $w_{b1} + w_{b2} = 1$, such that the price indices are $p_a = w_{a1}p_1 + w_{a2}p_2$ and similarly for b. Letting $dp_1 = dp_2$ be the (marginal) increases in the individual product prices, we have $dp_a = w_{a1}dp_1 + w_{a2}dp_2 = (w_{a1} + w_{a2})dp_1 = dp_1 = w_{b1}dp_2 + w_{b2}dp_1 = dp_b$.

category k (by means of a price change)—i.e. marginal revenue mr_{fk} plus marginal externality on other categories me_{fk}—is equal to marginal cost mc_{fk}. Note that the marginal externality imposed on any category $k' \neq k$ is the product of its markup $[p_{fk'} - mc_{fk'}]$ and the cross-category diversion ratio

$$\frac{\partial Q_{fk'}}{\partial p_{fk}} \Big/ \frac{\partial Q_{fk}}{\partial p_{fk}} \tag{29}$$

which is the change in category k' demand at firm f for every unit of demand it loses on category k as a result of an increase in p_{fk}. Dividing (28) by price we obtain the Lerner Index measure of market power

$$\frac{p_{fk} - mc_{fk}}{p_{fk}} = \left(-\frac{\partial Q_{fk}}{\partial p_{fk}} \frac{p_{fk}}{Q_{fk}}\right)^{-1} - \frac{\chi_f}{p_{fk}} \sum\nolimits_{k' \neq k} \left\{ \frac{\frac{\partial Q_{fk'}}{\partial p_{fk}}}{\frac{\partial Q_{fk}}{\partial p_{fk}}} [p_{fk'} - mc_{fk'}] \right\}. \tag{30}$$

This shows the relationship between market power and the cross-category externality: an independent category seller has a Lerner index that is equal to the inverse of its own-price elasticity, while a supermarket's Lerner index is lower by the extent of the marginal externality (as a proportion of p_{fk}).

6.2 Estimated Own- and Cross-Category Elasticities

The elasticities implied by the demand model are presented in Table 7 for six categories and three firms. The table consists of nine blocks of 6×6 sub-matrices. The three 6×6 within-firm elasticity matrices along the principal diagonal of the overall matrix give own- and cross-elasticities between the categories of a given firm. Note that all the elasticities in these blocks are negative, so that any pair of categories at the same firm are pricing complements. This in turn implies that the diversion ratio (29) and the cross-category externality in (30) are positive.

The principal diagonal in each of the within-firm elasticity matrices gives own-price elasticities—i.e. same-firm same-category price elasticities. These are generally larger in magnitude than the cross-category same-firm price elasticities (which are on the off-diagonals); this difference is a consequence of two consumer responses that are allowed in the consumer model (shown in equation (12)): (i) a reduction (at the intensive margin) in the continuous demand for the category holding store choices fixed and (ii) a change of store for the category but not for other categories, which is possible for two-stop shoppers (response class (2b) in subsection 3.2).

Two further features of the own-price elasticities are noteworthy. First, they have less than unit magnitude in some cases. Elasticities of less than unit magnitude are inconsistent with positive marginal costs for a single-category seller (see (30) for the case of $\chi_f = 0$). Elasticities of this magnitude are however consistent with positive marginal costs when the firm internalizes a positive externality on other categories (see (30) for $\chi_f = 1$), which results in the firm setting prices at a lower level than otherwise. Second, the own-price elasticities

Table 7: Cross Elasticities at Category-Firm Level for Selected Categories and Firms

	ASDA						Tesco						Aldi					
	Bakry	Drink	Fr,vg	H'hld	Meat	Milk	Bakry	Drink	Fr,vg	H'hld	Meat	Milk	Bakry	Drink	Fr,vg	H'hld	Meat	Milk
ASDA																		
Bakery	-0.72	-0.24	-0.36	-0.30	-0.51	-0.05	0.11	0.09	0.14	0.11	0.18	0.02	0.01	0.01	0.02	0.01	0.01	0.00
Drink	-0.17	-1.34	-0.29	-0.28	-0.41	-0.05	0.06	0.17	0.12	0.10	0.15	0.02	0.00	0.02	0.01	0.01	0.01	0.00
Fr,veg	-0.19	-0.21	-0.84	-0.27	-0.44	-0.04	0.06	0.08	0.20	0.10	0.16	0.02	0.01	0.01	0.03	0.01	0.01	0.00
H'hold	-0.18	-0.23	-0.30	-1.36	-0.43	-0.05	0.07	0.09	0.12	0.23	0.17	0.02	0.01	0.01	0.01	0.02	0.01	0.00
Meat	-0.19	-0.21	-0.31	-0.27	-1.18	-0.04	0.07	0.08	0.12	0.10	0.26	0.02	0.00	0.01	0.01	0.01	0.02	0.00
Milk	-0.17	-0.24	-0.28	-0.29	-0.42	-1.52	0.06	0.09	0.12	0.11	0.16	0.04	0.00	0.01	0.01	0.01	0.01	0.00
Tesco																		
Bakery	0.07	0.06	0.09	0.08	0.12	0.01	-0.76	-0.22	-0.35	-0.29	-0.47	-0.06	0.01	0.01	0.01	0.01	0.01	0.00
Drink	0.04	0.11	0.07	0.07	0.10	0.01	-0.15	-1.31	-0.28	-0.26	-0.37	-0.05	0.00	0.01	0.01	0.01	0.00	0.00
Fr,veg	0.05	0.05	0.12	0.07	0.11	0.01	-0.17	-0.20	-0.92	-0.26	-0.41	-0.05	0.00	0.01	0.02	0.01	0.01	0.00
H'hold	0.04	0.06	0.07	0.14	0.11	0.01	-0.16	-0.21	-0.30	-1.29	-0.39	-0.06	0.00	0.01	0.01	0.02	0.01	0.00
Meat	0.05	0.05	0.08	0.07	0.18	0.01	-0.17	-0.20	-0.30	-0.26	-1.15	-0.05	0.00	0.00	0.01	0.01	0.01	0.00
Milk	0.04	0.05	0.06	0.07	0.10	0.11	-0.15	-0.22	-0.28	-0.27	-0.38	-1.16	0.00	0.00	0.01	0.01	0.00	0.00
Aldi																		
Bakery	0.21	0.11	0.21	0.15	0.21	0.02	0.20	0.11	0.21	0.16	0.21	0.02	-1.23	-0.39	-0.68	-0.56	-0.46	-0.05
Drink	0.08	0.30	0.16	0.14	0.15	0.02	0.08	0.31	0.17	0.15	0.16	0.02	-0.21	-2.19	-0.52	-0.50	-0.34	-0.06
Fr,veg	0.09	0.09	0.32	0.13	0.18	0.01	0.08	0.09	0.34	0.13	0.17	0.02	-0.23	-0.32	-1.49	-0.44	-0.36	-0.05
H'hold	0.08	0.11	0.16	0.31	0.16	0.02	0.09	0.11	0.18	0.35	0.18	0.02	-0.23	-0.37	-0.54	-2.07	-0.36	-0.06
Meat	0.10	0.11	0.20	0.15	0.44	0.02	0.11	0.11	0.21	0.16	0.48	0.02	-0.28	-0.37	-0.65	-0.53	-2.25	-0.06
Milk	0.07	0.11	0.15	0.15	0.14	0.06	0.09	0.13	0.18	0.18	0.18	0.07	-0.22	-0.41	-0.55	-0.55	-0.39	-2.01

Notes: Each cell is elasticity of row demand with respect to column price. Derivatives calculated with finite differences for the 2000 households used in estimation.

vary across firms in a plausible way: they are higher for the discounter (Aldi) than for the Big Four firms, reflecting (i) the relatively high share of two-stop shoppers among the discounter's customers (with their greater ease of substituting a category between stores) and (ii) the relatively high price-sensitivity of consumers attracted to discounter firms.

The off-diagonal 6×6 blocks give inter-firm elasticities. These are asymmetric in magnitude because of the differences in firm market shares: the effect of prices at Aldi (which has small market share) on demands at ASDA or Tesco (which have a large market share) are small (e.g. see the top-right 6×6 block) compared to the opposite price elasticities. Note that the pattern of elasticities within these off-diagonal blocks suggest there is a significant number of two-stop consumers that switch firms only for the category affected by the price change (the "middle" response in the decomposition in equation (12))—e.g. in the top-middle block a change in the price of Tesco Meat has a higher proportional effect on ASDA Meat (0.26) than ASDA Drink (0.15) because of two-stop shoppers that switch stores for Meat only.

6.3 Profit Margin Calculations and External Validation

To estimate cross-category externalities we require marginal costs mc_{fk}. We obtain them by solving the system of first order conditions (28) for the case where retailers internalize cross-category effects (i.e. $\chi_f = 1$). Panel A of Table 8 reports the profit margin (i.e. Lerner index) implied by these marginal costs, for each category and a selection of firms. The first column gives the average Lerner index across categories; the average of this across firms is 0.31. Profit margins are highest for the Big Four firms, which is not surprising given their large share of the market.

An external check on the validity of the estimated price elasticities is given by comparing the profit margins implied by the model with profit margin data from CC (2000, 2008). Our precision is limited by two factors: (i) alternative assumptions are possible in deciding which cost components to count as marginal, and (ii) the theory of retail pricing suggests two models—efficient pricing and double marginalization—with alternative implications for the marginal costs perceived by a retailer.[35] Using information published in the CC's reports on the industry, we calculate a range from 16% to 52% on average across all categories, depending on the assumptions made under headings (i) and (ii).

A more precise external check is available by focusing on one of the product categories. The CC reports include profit margin figures specifically for the milk category, where marginal costs are relatively transparent. These figures imply a range for relevant profit margins from 20% to 34% using the same set of assumptions under headings (i) and (ii). The profit

[35] With efficient pricing the retailer optimizes against the joint marginal costs of the manufacturer and the retailer, while with double marginalization the retailer optimizes against the wholesale price. There is relatively little evidence on this issue, though Villas-Boas (2007) and Bonnet and Dubois (2010) directly compare the two modelling assumptions and their evidence rejects double marginalization and supports efficient pricing.

Table 8: Profit Margins and Cross-Category Externalities

	All	Bakery	Dairy	Drink	Dry	Fr,Veg	Hhold	Meat	Milk
A: Profit Margins $(p_{fk} - mc_{fk})/p_{fk}$									
All firms	0.31	0.34	0.22	0.26	0.36	0.44	0.26	0.34	0.22
Big Four	0.32	0.35	0.21	0.28	0.37	0.46	0.27	0.36	0.22
ASDA	0.35	0.38	0.28	0.29	0.38	0.54	0.27	0.39	0.21
Tesco	0.37	0.38	0.20	0.33	0.43	0.51	0.31	0.42	0.31
Aldi	0.23	0.23	0.20	0.20	0.21	0.40	0.22	0.14	0.17
M&S	0.27	0.32	0.26	0.32	0.26	0.23	0.21	0.28	0.22
B: Inverse Own-Category Elasticity (Absolute Value)									
All firms	0.81	1.15	0.70	0.64	0.97	0.94	0.67	0.70	0.65
C: Marginal Externality me_{fk}/p_{fk}									
All firms	0.50	0.81	0.49	0.37	0.61	0.50	0.41	0.36	0.42
Big Four	0.54	0.88	0.51	0.40	0.66	0.54	0.43	0.40	0.43
ASDA	0.54	1.01	0.68	0.46	0.72	0.64	0.46	0.45	0.44
Tesco	0.59	0.95	0.45	0.44	0.74	0.58	0.46	0.45	0.56
Aldi	0.35	0.58	0.40	0.25	0.40	0.27	0.26	0.30	0.33
M&S	0.36	0.27	0.26	0.32	0.26	0.23	0.21	0.28	0.22

Notes: Profit margins and externalities implied by the model in Nash equilbrium (with cross-category internalization). Averages in column "All" and rows "All Firms" and "Big Four" are revenue-weighted. By equation (30) figures in Panel B are the sum of those in Panels A and C (up to rounding error). We use the same 2000 consumers and taste draws used in estimation.

margins derived from our model for the milk category again fall inside this range, which provides further validation of the model. Further details of the calculations in this subsection are in Appendix D.

6.4 Cross-Category Externalities and Market Power

With elasticities and profit margins in hand we compute cross-category externalities. Recall from equation (30) that the Lerner index is the category's inverse elasticity minus its externality on other categories as a fraction of p_{fk}. We report these two components in Table 8: the inverse elasticity in Panel B and the marginal cross-category externality in Panel C. (Panel B is the sum of the corresponding figures in Panels A and C; we report only the all-firm averages to save space).

Note that the inverse elasticities in Panel B are the profit margins that we would have obtained if we had assumed that observed prices are generated by independent category sellers rather than supermarkets (i.e. if we had set $\chi_f = 0$ in (30) to back out marginal costs). As these are more than double the profit margin figures in Panel A we conclude (i) that the assumption of supermarket pricing fits the external profit margin data (in the previous subsection) much better than that of independent sellers, and (ii) that ignoring cross-category effects can result in market power being significantly overestimated.

The marginal externality reported in the table is a measure of the extent to which competition is intensified by supermarket organization. It can be interpreted as the (Pigouvian) marginal subsidy that must be offered to an independent seller to induce him to set prices that maximize the profits of the supermarket as a whole. The marginal externality is thus analogous to "upward pricing pressure" concept (see Farrell and Shapiro (2010)) that is used in antitrust policy to measure the anti-competitive effects from a merger of two substitute products. Supermarket organization is analogous to the merger of category sellers selling complementary goods, and the marginal externality measures the downward pricing pressure implied by supermarket organization.

As Panel C reports, the marginal externality as a fraction of price, i.e. me_{fk}/p_{fk}, is 0.5 on average across firms and categories. The positive sign of the externality indicates that in supermarket mode firms set prices closer to the competitive level than would be the case under independent category sellers, and its magnitude indicates that this pro-competitive effect is economically significant.[36] As a benchmark for how significant the effect is we note that it is greater than the magnitudes conventionally used to identify problematic merger cases (see CC (2011, Chapter 4) for a discussion).

Comparing the externalities for different categories we see that, while there is some variation, they are of a similar magnitude, and market power abated to a similar degree, even though the categories vary in how large a share they are of consumer budgets. A small category is capable of generating a similar marginal externality to a large one because it is the diversion *ratio* (29)—i.e. the demand effect on other categories per unit of demand lost on the category—that is important in determining the size of the externality (see equation 30) not the absolute effect on the demand of the other categories. This suggests that cross-category effects can be important even when studying pricing incentives for a category that is a small fraction of the consumer's budget.

Panel C also reports the externalities by firm. Externalities are substantial for all firms but there is some variation. In particular the Big Four firms have larger externalities than other firms. This is in part a consequence of their higher profit margins (as reported in Panel A) but may also derive from the fact that a greater proportion of their customers are one-stop shoppers, who generate larger cross-category effects per marginal shopper. We explore the competitive implications of alternative shopper types in the next subsection.

6.5 Competitive Implications of Alternative Shopper Types

We now analyze the price responses of two types of shopper with the goal of comparing their impact on the market power of the firms in the market. The two shopper types are those

[36] It is useful to conduct an intuition check for the magnitude of the marginal externality. Suppose all categories have identical prices and profit margins are 30% of price for all k (as we have estimated). Then from equation (28) a marginal externality as a fraction of price (me_{fk}/p_{fk}) of 0.5 implies a total same-firm diversion ratio $\sum_{k'\neq k} (\partial Q_{fk'}/\partial p_{fk}) / (\partial Q_{fk}/\partial p_{fk})$ of 1.67, i.e. if one unit of demand for k is lost to f because of an increase in p_{fk}, a total of 1.67 units of demand are lost across all other categories. Given the presence of one-stop shoppers in our setting this is an intuitively plausible diversion ratio. For further numerical calculations along these lines, and a discussion, see Nalebuff (2000).

Table 9: Demand and Profit Effect of a Price Increase: Decomposition by Shopper Type

		Category and Firm Type with Δp_{fk}							
		Drink		Fruit & Veg.		Household		Meat	
		Big 4	Disc	Big 4	Disc	Big 4	Disc	Big 4	Disc
A1: Proportion of Shoppers that are Marginal:									
(i) All shoppers	$100 \times \Delta D_{fk}/D_{fk}$	-10.0	-18.7	-7.1	-12.0	-10.0	-14.6	-9.22	-16.1
(ii) One-stop shoppers	$100 \times \Delta D^{1ss}_{fk}/D^{1ss}_{fk}$	-8.8	-19.2	-6.2	-12.8	-8.4	-12.9	-8.1	-15.7
(iii) Two-stop shoppers	$100 \times \Delta D^{2ss}_{fk}/D^{2ss}_{fk}$	-13.0	-18.2	-9.5	-11.5	-14.6	-16.7	-12.5	-18.4
A2: Decomposition of Marginal Shoppers in A1(i) (sum to 1):									
(1a) Initial one-stop shopper, drop firm altogether		0.28	0.19	0.53	0.49	0.30	0.34	0.56	0.50
(1b) Initial one-stop shopper, retain firm partially		0.35	0.26	0.12	0.08	0.31	0.16	0.09	0.12
(2a) Initial two-stop shopper, drop firm altogether		0.12	0.21	0.18	0.32	0.11	0.22	0.18	0.18
(2b) Initial two-stop shopper, retain firm partially		0.24	0.34	0.18	0.11	0.28	0.28	0.17	0.22
B: Cross-category diversion ratio	$\Sigma_{k' \neq k}\Delta D_{fk'}/\Delta D_{fk}$:								
(i) All shoppers		2.1	1.5	3.4	2.9	2.2	2.3	3.6	2.8
(ii) One-stop shoppers		2.7	2.5	4.4	3.7	2.9	3.6	4.8	3.8
(iii) Two-stop shoppers		1.1	0.9	1.6	1.7	1.0	1.1	1.6	1.3
C1: Total Effect on firm profit (as % of category revenue):									
	$100 \times \Sigma_k \Delta\pi_{fk}/R_{fk}$	-0.70	-1.58	-0.81	-0.69	-0.79	-1.16	-0.81	-1.47
C2: Decomposition by category (rows sum to C1)									
Category k profit	$100 \times \Delta\pi_{fk}/R_{fk}$	5.06	2.59	4.53	3.04	5.22	5.35	4.44	4.31
Other category profit	$100 \times \Sigma_{k' \neq k}\Delta\pi_{fk'}/R_{fk}$	-5.76	-4.17	-5.29	-3.73	-6.01	-6.51	-5.25	-5.78
C3: Decomposition by shopper type (rows sum to C1)									
One-stop shoppers	$100 \times \Delta\pi^{1ss}_f/R_{fk}$	-0.92	-2.51	-0.92	-1.09	-1.02	-2.14	-1.01	-2.65
Two-stop shoppers	$100 \times \Delta\pi^{2ss}_f/R_{fk}$	0.22	0.93	0.16	0.40	0.23	0.98	0.20	1.18

Notes: For each category and firm the price p_{fk} is increased unilaterally by 10 percent holding all other prices constant. We do this separately for all four of the Big Four firms and all three of the Discounter firms. The figures in the table are the simple average of the demand responses for each of these two groups of firms. The decomposition in Panel A2 corresponds to the classification in subsection 3.2. The predictions use the observations and taste draws for the 2000 consumers used in estimation.

that use only one firm and those that use two; we call these one-stop and two-stop shoppers respectively.[37] We noted in the simple example in Section 3.2 that the relative impact on market power of these shopper types hinges on the following two factors: (i) the proportion of shoppers that are marginal and (ii) the cross-category externality per marginal shopper.

In Table 9 we decompose the effects of a series of small price increases into their impact on one-stop and two-stop shoppers. We consider Big Four and Discounter firms separately since they differ in the proportion of one-stop shoppers in their customer mix. We consider unilateral 10% price increases for specific categories and firms. The total number of shoppers D_{fk} at firm f for category k (defined in 26) is decomposed as follows $D_{fk} = D_{fk}^{1ss} + D_{fk}^{2ss}$ where D_{fk}^{1ss} are one-stop shoppers and D_{fk}^{2ss} are two-stop shoppers. Let $\Delta D_{fk} = \Delta D_{fk}^{1ss} + \Delta D_{fk}^{2ss}$ be the number these shoppers that are "marginal" in the sense that they stop buying category k from firm f in response to the price increase.

Panel A1 shows that two-stop shoppers are more likely to be marginal than one-stop shoppers. This is in line with intuition, as a two-stop shopper can switch categories between the firms he visits without incurring shopping costs. Panel A2 gives a decomposition of marginal shoppers ΔD_{fk} into the four discrete response classes discussed in Section 3.2. All of the response classes are empirically significant, including the response class (1a) that has maximal cross category effects, i.e. one-stop shoppers that leave firm f altogether, and the class (2b) that has minimal cross-category effects, i.e. two-stop shoppers that retain firm f for other categories.

Panel B presents a simple measure of the cross category demand effects per marginal shopper: the cross-category diversion ratio in terms of shoppers, i.e.

$$\sum\nolimits_{k' \neq k} \Delta D_{fk'} / \Delta D_{fk} \ , \tag{31}$$

where $\Delta D_{fk'}$ for $k' \neq k$ is the number of shoppers firm f loses on categories $k' \neq k$ in response to the price change. The ratio is thus the total number of shoppers lost by firm f for other categories per marginal shopper for category k. Rows B(ii, iii) show that this ratio is higher for one-stop shoppers than two-stop shoppers, i.e. on average a marginal one-stop shopper generates larger cross-effects than a marginal two-stop shopper.

These findings contribute to some interesting differences between firms. Firms that have a high proportion of one-stop shoppers in their customer mix (i.e. the Big Four) tend to have relatively few marginal shoppers (row A1(i)), but these marginal shoppers tend to have relatively large cross-category demand effects (row B(i)). This contributes to the relatively

[37] Up to now we have used the term one-stop shopper to refer to a shopper using two stores, regardless of whether they are operated by the same firm. It is natural in the analysis of pricing incentives in our empirical application to define one-stop shopping in terms of the number of firms (rather than stores) used given that firms set national prices in their stores, which means that a consumer shopping at two stores belonging to the same firm cannot avoid a price increase by switching a category between these stores, in the sense described for response class 2b in subsection 3.2. Most of the policy discussion surrounding cross-shopping and multi-stop shopping discussed in the introduction related to the competitive consequences of shoppers using different firms in the same shopping period.

large marginal externalities for Big Four firms in Table 8.

Panel C analyzes the impacts on profit. π_f is the profit of the firm and is the sum of the profits $\pi_{fk} = Q_{fk}(p)\,[p_{fk} - mc_{fk}]$ from each category. We present the change in profit $\Delta\pi_f$ as a proportion of firm-category revenue $R_{fk} = p_{fk}Q_{fk}$ to help us judge the magnitude of the change. Panel C1 shows that the effect on total profit $\Delta\pi_f$ is negative; this is true by construction since we assume that the firm sets prices to maximize π_f. The next two rows (in C2) separate the total profit effect into the own-category $\Delta\pi_{fk}$ and the cross-category $\sum_{k'\neq k}\Delta\pi_{fk'}$ profit effects, which add to give the total effect in C1. Profits earned from category k increase by about 5% of firm-category revenue, but profits earned on the other categories fall by a slightly larger amount; this confirms that delegation of pricing to an independent category seller would increase prices.

We can now evaluate which shopper type has the greater pro-competitive effect. To do this we separate the change in the firm's profits $\Delta\pi_f$ into the change in the profit earned from one-stop shoppers $\Delta\pi_f^{1ss}$ and the change $\Delta\pi_f^{2ss}$ from two-stop shoppers ($\Delta\pi_f = \Delta\pi_f^{1ss} + \Delta\pi_f^{2ss}$). Panel C3 shows the average effect on profit for two groups of firms, Big Four and Discounters. We find that for both types of firm the average effect of the price increase on the profit from one-stop shoppers $\Delta\pi_f^{1ss}$ is negative while the average effect on the profit from two-stop shoppers $\Delta\pi_f^{2ss}$ is positive. Thus the one-stop shoppers constrain supermarket pricing more than the two-stop shoppers.

The results elsewhere in the table indicate that this finding is obtained because (i) one stop shoppers generate larger cross-category effects per marginal consumer than two-stop shoppers, and (ii) this outweighs the lower proportion of one-stop shoppers that are marginal. The finding suggests that it is appropriate for antitrust authorities to focus their attentions on the state of competition for one-stop shoppers, even though the customer mix of the retailers includes a significant proportion of two-stop shoppers who can substitute categories between stores without incurring shopping costs.

The structure of the model allows us to consider pricing questions that extend beyond the setting of a simple linear firm-category price. We briefly consider loyalty discounts as these relate closely to the issues that motivate this paper. In Table 10 we report the effect of price increases that affect either one-stop shoppers or two-stop shoppers but not both.[38] Consumers that buy products exclusively from one firm thus pay prices p_{fk}^{1ss} and those that cross-shop at different stores pay prices p_{fk}^{2ss}. Consider a price change of 2% to all category prices so that either $\Delta p_{fk}^{1ss} = 2\%$ or $\Delta p_{fk}^{2ss} = 2\%$ for all k. The first row of Panel A shows the change in the total number of category-firm shoppers $\Sigma_k \Delta D_{fk}$ expressed as a percentage of affected shoppers $\Sigma_k D_{fk}^{nss}$, where $nss \in \{1ss, 2ss\}$. The next two rows decompose the change into the number of shoppers of each type, and shows that significant numbers of consumers convert from one-stop to two-stop shopping (or vice versa) as a result of the price change. Panel B shows that firms lose profit if they raise prices to their core one-stop shoppers and

[38] See Armstrong and Vickers (2010) for a theoretical discussion of the profit incentives and welfare impacts of loyalty discounts in a model of multi-category multi-retailer competition.

Table 10: Price Discrimination by Shopper Type

		Shopper Group with Δp			
		1-stop ($nss = 1ss$)		2-stop ($nss = 2ss$)	
		Big Four	Disc	Big Four	Disc
A: % Change in Category-Firm Shoppers (as proportion of $\Sigma_k D_{fk}^{nss}$)					
All Shoppers	$100\times\frac{\Sigma_k \Delta D_{fk}}{\Sigma_k D_{fk}^{nss}}$	-6.06	-11.46	-5.14	-6.71
One-stop shoppers	$100\times\frac{\Sigma_k \Delta D_{fk}^{1ss}}{\Sigma_k D_{fk}^{nss}}$	-6.65	-11.96	1.83	0.61
Two-stop shoppers	$100\times\frac{\Sigma_k \Delta D_{fk}^{2ss}}{\Sigma_k D_{fk}^{nss}}$	0.59	0.49	-6.97	-7.33
B: Effect on Firm profit (as a proportion of revenue)					
Overall profit change	$100\times\frac{\Delta\pi_f}{R_{fk}}$	-0.16	-0.35	0.06	0.22
Positive profit change indicator	$1[\Delta\pi_f > 0]$	0	0	1	1

Notes: All category prices are jointly increased by 2 percent for each f either to one-stop or to two-stop shoppers, holding other prices constant. The figures are simple averages of the demand responses for firms in each of two groups (Big Four and Discounter). Predictions are for the sample of 2000 consumers (and the same taste draws) used in estimation.

gain profits when the raise them to two-stop shoppers. Part of the profit gain in the latter case is because some of the two-stop shoppers are induced to become one-stop shoppers, which in turn results in the shopper buying more categories in total from the firm.

7 Conclusions

In many important competitive settings, such as retailing, customers buy multiple categories and many prefer to do so from the same location or firm. We develop for estimation a multi-store multi-category model of consumer demand which belongs to a class that is relevant for the analysis of pricing in such settings. We estimate the model using data from the supermarket industry in the UK. We use the estimated model to analyze two policy-relevant questions: (i) the implications of the internalization of cross-category externalities for the market power of supermarkets and (ii) the relative impact of one-stop and two-stop shoppers on equilibrium prices.

The cross-category elasticities we estimate imply that supermarket organization substantially mitigates market power. This has implications for the analysis of retail pricing at two levels. First, at a single-category level of analysis, it indicates a role for considering cross-category effects when using demand elasticities to analyze prices for a given category of interest. In our application we found that accounting for cross-category effects implies a Lerner index typically less than half as large as the Lerner index that would be implied with independent category sellers, so that ignoring cross-category effects can result in market power being overestimated significantly.

Second, at a broader level, the results are relevant for analysis of the organization of the retail industry. Supermarket competition has received much attention—in part because of the large size of firms such as Walmart, Carrefour and Tesco—and policies are sometimes introduced with the aim of protecting or promoting alternative ways of organizing the industry: e.g. planning laws in the UK were tightened in the 1990s to protect town centre retailing, while in France a law (*Loi Raffarin,* 1996) imposed floor space limits on supermarkets with the objective of protecting small traditional retailers. Our empirical results highlight the pro-competitive nature of supermarket pricing relative to alternative ways of organizing retail supply in which pricing is decentralized to independent category sellers.

Comparing one-stop and two-stop shoppers we find that when supermarkets increase the price of a category marginally they lose the profits earned on one-stop shoppers and gain profits from two-stop shoppers, which implies that one-stop shoppers constrain supermarket prices more than two-stop shoppers. This finding suggests it can be appropriate for antitrust authorities to focus on competition for a firm's one-stop (or core) shoppers even where there are many multi-stop shoppers in the firm's customer mix. This is consistent with the position adopted by the FTC in the recent Whole Foods/Wild Oats antitrust case where the question was whether to allow the merger of firms that compete for the same group of core shoppers, when the firms also sell to two-stop (or cross-) shoppers. More generally the finding indicates that the presence of consumers that shop in several stores does not necessarily promote competitive pricing incentives.

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A Online Appendix: Category Definitions

TNS assigns to each transaction the variable "Retailer Share Track (RST) Market Code" that correspond to 269 narrowly defined product groups. We define our eight categories as follows where the names of product groups (including abbreviations) are those of TNS.

1. *Bakery*: Ambient Pizza Bases, Ambient Cakes and Pastries, Ambient Christmas Pudding, Ambient Sponge Puddings, Canned Rice Puddings, Childrens Biscuits, Chilled Breads, Chilled Cakes, Chilled Desserts, Chilled Pizza and Bases, Crackers & Crispbreads, Everyday Biscuits, Fresh/Chilled Pastry, Frozen Bread, Frozen Savoury Bakery, Healthier Biscuits, Morning Goods, Savoury Biscuits, Seasonal Biscuits, Tinned Sponge Puddings, Toaster Pastries, Total Bread.

2. *Dairy*: Butter, Defined Milk and Cream Products, Fresh Cream, Fromage Frais, Instant Milk, Margarine, Total Cheese, Total Ice Cream, Yoghurt, Yoghurt Drinks And Juices.

3. *Drink*: Ambient One Shot Drinks, Ambient Fruit or Yoghurt Juice and Drnk, Beer and Lager, Bottled Colas, Bottled Lemonade, Bottled Other Flavours, Bottled Shandies, Canned Colas, Canned Lemonade, Canned Other Flavours, Canned Shandies, Chilled One Shot Drinks, Cider, Fabs, Food Drinks, Fortified Wines, Ginger Ale, Lemon and Lime Juices, Mineral Water, Soda Water, Sparkling Wine, Spirits, Tonic Water, Wine.

4. *Dry*: Ambient Condiments, Ambient Slimming Products, Ambient Vegetarian Products, Artificial Sweetners, Breakfast Cereals, Chocolate Biscuit Bars, Chocolate Confectionery, Chocolate Spread, Confectionary. & Other Exclusions, Cooking Oils, Crisps, Dry Meat Substitutes, Dry Pasta, Dry Pulses and Cereal, Ethnic Ingredients, Everyday Treats, Flour, Frozen Confectionery, Gum Confectionery, Herbal Tea, Herbs and Spices, Home Baking, Honey, Instant Coffee, Lards and Compounds, Liquid and Ground Coffee and Beans, Mincemeat (Sweet), Mustard, Packet Stuffing, Peanut Butter, Pickles Chutneys & Relish, Powder Desserts & Custard, Preserves, RTS. Custard, Ready To Use Icing, RTS Desserts Long Life, Salt, Savoury Snacks, Sour and Speciality Pickles, Special Treats, Suet, Sugar, Sugar Confectionery, Sweet and Savoury Mixes, Syrup & Treacle, Table Sauces, Table and Quick Set Jellies, Tea, Vinegar.

5. *Fruit and Vegetables*: Ambient Olives, Ambient Rice and Savoury Noodles, Ambient Salad Accompaniment, Baked Bean, Bitter Lemon, Canned Fish, Canned Hot Meats, Canned Salads, Canned Vegetables, Chilled Fruit Juice and Drink, Chilled Olives, Chilled Prepared Fruit and Veg, Chilled Prepared Salad, Chilled Rice, Chilled Salad Accompaniment, Chilled Vegetarian, Cous Cous, Frozen Potato Products, Frozen Vegetables, Frozen Vegetarian Prods, Fruit, Instant Mashed Potato, Nuts, Prepared Peas & Beans, Tinned Fruit, Tomato Products, Total Fruit Squash, Vegetable.

6. *Household*: Air Fresheners, Anti-Diarrhoeals, Antiseptics & Liq. Disinfectant, Bath Additives, Batteries, Bin Liners, Bleaches & Lavatory Cleaners, Body Sprays, Carpet Cleaners/Stain Removers, Cat Litter, Cat and Dog Treats, Cleaning Accessories, Cold Sore Treatment, Cold Treatments, Conditioners and Creme Rinses, Contact Lens Cleaners, Cotton Wool, Cough Liquids, Cough Lozenges, Decongestants, Dental Floss or Sticks, Dentifrice, Denture Cleaners/Fixature, Deodorants, Depilatories, Dog Food, Electric Light Bulbs, Eye Care, Fabric Conditioners, Facial Tissues, First Aid Dressings, Foot Preparations, Furniture Polish, Hair Colourants, Hairsprays, Hand Wash Products, Hayfever Remedies, Home Perms, Household Cleaners, Household Food Wraps, Household Insecticides, Incontinence Products, Indigestion Remedies, Kitchen Towels, Laxatives, Liquid Soap, Machine Wash Products, Mens Hairsprays, Mens Mass Fragrances, Mens Skincare, Moist Wipes, Mouthwashes, Oral Analgesics, Oral Lesion/teething, Pot Pourri and Scented Candles and Oils, Razor Blades, Sanpro, Shampoo, Shaving Soaps, Shoe Care Products, Skincare, Sleeping Aids, Sun Preparations, Talcum Powder, Toilet Soap inc. Mens, Toilet Tissues, Topical Analgesics, Topical Antiseptics, Total Cat Food inc. Bulk, Total Dry Dog Food, Total Male and Female Styling, Total Toothbrushes, Upset Stomach Remedies, Vitamin and Mineral supplements, Wash Additives, Washing Up Products.

7. *Meat*: Ambient Cooking Sauces, Ambient Dips, Ambient Pastes and Spreads, Ambient Sandwich Fillers, Ambient Soup, Canned Pasta Products, Chilled Black and White Pudding, Chilled Burgers and Grills, Chilled Cooking Sauces, Chilled Dips, Chilled Gravy and Stock, Chilled Pate and Paste and Spread, Chilled Prepared Fish, Chilled Processed Poultry, Chilled Ready Meals, Chilled Sausage Meat, Chilled Frankfurter/Continental Sausages, Chilled Sandwich Fillers, Cold Canned Meats, Complete Dry/Ambient Meals, Cooked Meats, Cooked Poultry, Fresh Bacon Joint, Fresh Bacon Rashers, Fresh Bacon Steaks, Fresh Beef, Fresh Flavoured Meats, Fresh Lamb, Fresh Other Meat & Offal, Fresh Pasta, Fresh Pork, Fresh Poultry, Fresh Sausages, Fresh Soup, Frozen Bacon, Frozen Beef, Frozen Cooked Poultry, Frozen Fish, Frozen Flavoured Meats, Frozen Lamb, Frozen Meat Products, Frozen Other Meat & Offal, Frozen Pizzas, Frozen Pork, Frozen Poultry, Frozen Processed Poultry, Frozen Ready Meals, Frozen Sausage Meat, Frozen Sausages, Hens Eggs, Instant Hot Snacks, Loose Fresh Meat & Pastry, Meat Extract, Other Chilled Convenience, Other Frozen Foods, P/P Fresh Meat and Veg and Pastry, Packet Soup, Shellfish, Wet or Smoked Fish.

8. *Milk*: Total Milk.

B Online Appendix: Price Index Construction

The prices used in the model are computed at category-week-store-demographic group level for categories $k = 1, .., 8$ using the full sample of transactions in the TNS data. In data there are two levels of aggregation below category k. First, in each category k (e.g. "Household Goods"), there is a set of narrowly-defined product groups g (e.g. "Shampoo") listed in Appendix A. We drop some minor product groups that are not sold by all firms, which leaves 183 (out of 268) product groups that account for 96% of consumer expenditure. We define this set of product groups $\mathcal{G}_k$ for each k. In each product group $g \in \mathcal{G}_k$ there is a set of products h, each of which is a unique product and pack size (e.g. "Herbal Essences Fresh Balance Shampoo 200ml" is a product in the "Shampoo" group). Products h are numerous and there is a tail of products with low volume. For each firm f we select products h that appear in the data at least once in all years (2002-2005) and in more than six quarterly periods. This yields a set of products, $\mathcal{H}_{fg}$, for each firm f and product group g. For each store j product h and week t we compute price p_{jht} as the median price of product h for week t for stores operated by store j's firm $f(j)$. As noted in Section 2 the predominant pricing practice is national pricing, in which firms do not vary prices depending on the location of their stores. In cases where there are no observed prices for a particular week we impute the price using the median price for the quarter-year in which week t falls. The Big Four firms (as listed in Table 3) have heterogeneous store sizes. To allow for the possibility they set different prices for different store sizes, we compute median price separately for two store size classes by sales area: small (less than or equal to $40,000$ square feet) and large (greater than $40,000$ square feet). In practice this leads to insignificant differences. We thus obtain 17 firm-level prices for each t and h: two prices by store size class for each of the Big Four firms (giving eight prices), and a single price for eight other chains (M&S, Waitrose, Aldi, Lidl, Netto, Iceland, Co-op, Somerfield, and Other (i.e. smaller chains)).

The aggregation to category k level proceeds in two stages: (i) from product h to product group g and (ii) from product group g to category k. In each of these stages we weigh the prices to reflect their importance using information from the transactions data. We compute weights separately for eight demographic types $m = 1, .., 8$ which are combinations of social class and household size categories. The TNS household characteristics data has six social class levels $(1, ..., 6)$ based on occupational group. These social class indicators are used widely in United Kingdom as a measure of socioeconomic status. A lower number on this scale has a higher average household income. We combine social class level 1 and 2, and likewise 5 and 6, as there are relatively few households in these groups, which yields four social class categories. For each of these we divide housholds into two size groups—small (one or two people) and large (more than two people)—which yields the eight demographic types.

In the first stage of aggregation the product group g price in store j for week t and demographic group m is given by $p^m_{jgt} = \sum_{h \in \mathcal{H}_{gf(j)}} w^m_{hf(j)} p_{jht}$ where $w^m_{hf(j)}$ are volume weights. We use volume weights at this stage since there is a common volume unit for products within each g (e.g. volumes in "Shampoo" are in ml). If each product were sold in each firm then we could proceed using volume weights $w^m_{hf} = Q^m_h / Q^m_g$ where Q^m_h is the total volume of product h sold to demographic group m over the three year period and Q^m_g is the total volume sold in product group g to demographic group m over the three year period. However each product h is not sold by all firms so we instead compute $\tilde{w}_{hf}^m = Q_h^m / Q_{g|h}^m$ where $Q_{g|h}^m$ is the volume sold in product group g to demographic group m by firms selling product h and let $w_{hf}^m = \tilde{w}_{hf}^m \Big/ \sum_{h \in \mathcal{H}_{gf}} \tilde{w}_{hf}^m$ so that $\sum_{h \in \mathcal{H}_{gf}} w_{hf}^m = 1$ for any f. This weighs products using information that is not specific to firm f where products are sold by multiple firms stores and uses firm f specific information otherwise.

In the second stage of aggregation, the category price p_{jkt}^m is a revenue-weighted average of price ratios p_{jgt}^m / p_{bg}^m at product group level (where p_{bg}^m is an arbitrary base price):

$$p_{jkt}^m = \sum_{g \in \mathcal{G}_k} \omega_g^m \left(\frac{p_{jgt}^m}{p_{bg}^m} \right). \tag{32}$$

The weights ω_g^m are the total expenditure share (over the three year period) of each product group g by demographic type m and satisfy $\sum_{g \in \mathcal{G}_k} \omega_g^m = 1$ for each m. The weights are constant across stores and over time. Following common practice in price index construction (see for example Chapter 2 in ONS(2014)[39]) we (i) use sales rather than volume weights at this upper level of aggregation because the different product groups are often in different units, and (ii) use price ratios in (32) to ensure that p_{jkt}^m is independent of the units chosen within any product group. We set the arbitrary base price p_{bg}^m to be the price in the first week ($t = 1$) in the smaller size class of ASDA stores.

C Online Appendix: Category-Specific Variables used in Price Instrument

For each category we use a number of variables that we assume are correlated with the marginal cost of products in the category but are unaffected by demand shocks in Great Britain. They fall into two broad classes: first, the prices of inputs sold upstream from the retailer that are also traded internationally (so that their prices are determined by world rather than domestic markets), and, second, retail prices in Ireland, which we assume are related to retail prices in Great Britain via changes in marginal costs (similar to instruments used in Hausman et al. (1994)). The variables are from four sources: (i) The *Agricultural Price Index* published by the UK's Office for National Statistics (ONS) for United Kingdom agricultural outputs (i,a) and inputs (i,b); (ii) The *Producer Price Index* published by the ONS for goods bought and sold by United Kingdom manufacturers; (iii) the *Consumer Price Index* in Ireland published by the Central Statistical Office, Dublin; and (iv) three commodity milk price indices (known as IMPE, AMPE, MCVE) from DairyCo that measure the market value of raw milk in the United Kingdom. The variables used for each category

[39] Office for National Statistics (2014) "Consumer Price Indices Technical Manual", available at http://www.ons.gov.uk

are listed as follows where we give the variable name and note the source ((i,a) to (iv) as defined above).

1. *Bakery*: (i, a) Cereals, Crop products, Total of all products; (i, b) Feed Barley, Feed Oats, Feed Wheat; (ii) Food Products, Food Products—EU Imports, Food Products—Non EU Imports; (iii) Bread.

2. *Dairy* (i, a) Eggs, Milk, Total of all products; (i,b) Feed Barley, Feed Oats, Feed Wheat; (ii) manufacturer milk price; (iv) AMPE, IMPE, MCVE, Bulk Cream, Butter (Unsalted), EU farmgate milk price, Mature Cheddar Cheese, Mild Cheddar Cheese, Skimmed Milk Powder, Whey Powder.

3. *Drink* (i, a) Crop products; (ii) Alcoholic beverages including duty, Beer, Beer including duty, Beverages—EU imports, Beverages—non EU imports, Dairy products, Distilled Alcholoic Beverages, Fruit & vegetable juices, Processed & preserved fruit & vegetables, Soft drinks mineral waters & other bottled waters, Cocoa chocolate & sugar confectionery, Wine from grape & cider; (iii) Alcoholic beverages, Fruit, Non-alcoholic beverages, Sugar.

4. *Dry* (ii) Cocoa chocolate & sugar confectionery, Condiments & seasonings, Food products, Food Products - EU Imports, Food Products - Non EU Imports, Fruit & vegetable juices, Ice cream, Meat & poultry meat products, Mineral waters & other bottled waters, Other food products, Prepared meals & dishes, Preserved meat & meat products, Processed & preserved fish crustaceans & molluscs, Processed & preserved fruit & vegetables, Processed & preserved potatoes, Processed tea & coffee, Soft drinks mineral waters & other bottled waters, Wine from grape & cider; (iii) Bread, Meat, Dairy, Oils, Fruit, Vegetables, Sugar, Condiments, Soup, Other food.

5. *Fruit & Vegetables*: (i a) Cabbage, Cereals, Crop products, Dessert apples, Fresh fruit, Fresh vegetables, Lettuce, Oilseed rape, Onions, Other fresh vegetables, Other fresh fruit, Potatoes for consumption, Seeds, Sugar beet, Total of all products, Other crop products; (i b) Feed barley, Feed oats, Feed wheat; (iii) Fruit, Vegetables.

6. *Household goods*: (ii) Basic pharmaceutical products & pharmaceutical preparations - non EU imports, Cleaning & polishing preparations, Household & sanitary goods & toilet requisites, Paper stationery—EU imports, Paper stationery—non EU imports, Perfumes & toilet preparations, Perfumes & toilet preparations—EU imports, Pharmaceutical preparations, Prepared pet foods, Soap & detergents; (iii) Laundry goods, Health goods, Personal hygine goods.

7. *Meat*: (i a) Animal output, Crop output; (ii) Condiments & seasonings, Food products, Meat & poultry meat products, Other food products, Prepared meals & dishes,

Preserved meat & meat products, Processed & preserved fish crustaceans & molluscs, Processed & preserved fruit & vegetables, Processed & preserved potatoes, Food products—EU imports, Food products—non EU Imports; (iii) Bread, Condiments, Dairy, Meat, Oils, Soup, Sugar, Vegetables, Other food.

8. *Milk:* as Dairy.

D Online Appendix: Profit Margin Calculations

Gross retail margins m_r are defined as the difference between retail revenues and wholesale costs. Using data from the supermarkets' accounts across all grocery categories the Competition Commision (CC) reports gross retail margins in the range 0.24-0.25 of retail prices depending on firm (CC(2000) Table 8.19). Gross manufacturer margins m_m are defined as the difference between supplier revenues and supplier operating costs excluding labour costs as a proportion of manufacturer revenues. The CC reports gross manufacturer margins of 25% and 36%, depending on the sample of firms used (CC(2000) Paragraph 11.108 and CC(2008) Appendix 9.3 Paragraph 11). To obtain an upper bound to profit margins assume that labour costs are not marginal and that there is efficient retail pricing, so that the manufacturer's margin is included. Then these margin figures can be combined to give an overall vertical profit margin (as a proportion of retail prices) using the formula $m = m_r + (1 - m_r)m_m$ where m is the overall margin, m_r is retail margin and m_m is the manufacturer's margin. Using the higher of the two figures above ($m_r = 0.25$ and $m_m = 0.36$) this gives an (upper bound) figure of 52%. To obtain a lower bound we assume that all of labour costs are marginal costs and that there is double marginalization (inefficient retail pricing) so that the manufacturer's margin is be excluded. The CC reports that the ratio of labour costs to wholesale price costs is 9:83 (see CC(2000), Paragraph 10.3) which implies labour costs are $\frac{9}{83}\% = 10.8\%$ of wholesale costs. This implies we should adjust the retail gross margins reported above using the formula $m = 1 - (1 - m_r) * 1.108$ which gives 16% (using $m_r = 0.24$, the lower of the two figures above). Thus we have computed a lower bound of 16% and an upper bound of 52%. These bounds are conservative as it seems likely that some intermediate proportion of labour costs are marginal. In the case of the milk category the CC reports gross retail margins in the range 0.28-0.30 and gross manufacturer margins in the range 0.04-0.05 (see CC (2008) Appendix 9.3 Paragraphs 12 and 15). Using the same method these figures imply margin estimates in the range 20% to 34% for the milk category.