

## Multi-Category Competition and Market Power: A Model of Supermarket Pricing<sup>†</sup>

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*In many competitive settings, consumers buy multiple product categories, and some prefer to use a single firm, generating complementary cross-category price effects. To study pricing in supermarkets, an organizational form where these effects are internalized, we develop a multi-category, multi-seller demand model and estimate it using UK consumer data. This class of model is 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 consumers inclined to one-stop (rather than multi-stop) shopping have a greater pro-competitive impact because they generate relatively large cross-category effects. (JEL D12, L11, L13, L81)*

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 shopping behavior: a consumer who prefers to purchase all categories at a single store may generate larger cross-category effects than a shopper willing to use multiple stores, since the latter can easily switch stores only for the category affected by a price change and not for other categories.

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<sup>†</sup>Go to <https://doi.org/10.1257/aer.20160055> to visit the article page for additional materials and author disclosure statement(s).

Whether sellers internalize such cross-category effects depends on the organization of supply.<sup>1</sup> 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.<sup>2</sup> 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.<sup>3</sup>

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 one-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). 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 incompatible (i.e., have infinite *shopping costs*), so that consumers must buy only from one firm, than when they are not (see Matutes and Regibeau 1988, Economides 1989).

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. 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, Leonard, and Zona 1994; Nevo 2001; Sudhir 2001; Villas-Boas 2007; Bonnet and Dubois 2010), or too low because of a predatory intent or a negative consumption externality (see Griffith, Nesheim, and O'Connell 2015). The second is the level of the retailer as a whole, setting prices across a range of categories (see, for example, Chevalier, Kashyap, and Rossi 2003 and Smith 2004), which is the focus of 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 by the Federal Trade Commission (FTC)).<sup>4</sup> At this level there has been much interest in the growth of large retail firms such as Walmart and Carrefour (see Basker 2007 for a survey). 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

<sup>1</sup> A well-known example outside of retailing is the selling of component parts for an airplane. 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).

<sup>2</sup> 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.

<sup>3</sup> 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*, September 22, 2010). These arrangements are sometimes referred to as "stores within a store" or "in-store concessions."

<sup>4</sup> *FTC v. Whole Foods Markets, Inc.*, 533 F.3d 869 (D.C. Cir. July 29, 2008).

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 consumers who prefer one-stop shopping (i.e., to use a single store) constrain market power more than those who choose multi-stop shopping (who use multiple stores). This has been an important question in prominent antitrust investigations. One possibility is that the former—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 stores. 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. In the UK's CC inquiries into the supermarket industry, some firms claimed 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” (CC 2000, paragraph 2.31). 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” (CC 2000, paragraph 4.68). In the United States in the proposed Whole Foods/Wild Oats merger, the parties to the proposed merger argued that many of their customers *cross-shop* in a wide range of other firms, buying different categories from different stores, and that these multi-stop shoppers constrain 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 between retailers combined by multi-stop shoppers. In both cases, there was a debate as to which consumer type constrained supermarket prices more, with implications for whether a narrow or wide definition of the market was appropriate for competition analysis.

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 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 the prominence of this issue in the 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 on market power of consumers inclined to one-stop and multi-stop shopping. 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 purchases in a given shopping period. For each category a consumer makes a discrete choice of store(s), 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 benefit of multi-store shopping—going to the best store for each category—must be weighed against the fixed costs of using multiple stores. Consumers inclined to one-stop shopping either have relatively high shopping costs or view a single store as being the best for all categories.

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 store-category 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 that the consumer selects. To overcome 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.

The estimated parameters imply complementary pricing effects between categories sold by the same retailer. We calculate 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 one-half for most categories and firms. To quantify the externality between product categories (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 47 percent of the price of the category (on average across firms and categories).<sup>5</sup> This externality is analogous to the *pricing pressure* concept that measures the effects of a merger, introduced in Farrell and Shapiro (2010).<sup>6</sup> 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.

To assess whether consumer types inclined (because of their taste type) to one-stop shopping (at observed prices) have a greater competitive impact than those

<sup>5</sup>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, Pashigian, and Prendergast (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.

<sup>6</sup>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 1994). 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 a merger of substitutes.

inclined to two-stop shopping, we compare the effect of a marginal price change (for one firm and one category at a time) on the profits from each consumer group. We find that the profit from one-stop shopping types falls and profit from two-stop shopper types increases. This implies that the former have the greater pro-competitive impact. We find that this is a consequence of the greater cross-category effects of one-stop shopping types. Since shopping costs are an important determinant of one-stop shopping we also compare consumers by shopping costs and find similar results: we find that those with high shopping cost have a greater pro-competitive impact than those with low shopping costs. 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 shoppers inclined to one-stop shopping.

The theoretical literature makes extensive use of a multi-store multi-category modeling framework to study retail pricing. Some papers in this literature impose one-stop shopping (Stahl 1982; Beggs 1994; Smith and Hay 2005) while others model the multi-stop shopping decision (Klemperer 1992; Armstrong and Vickers 2010; Chen and Rey 2012).<sup>7</sup> 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) stores and makes a (continuous) nonnegative choice of quantity for every category. We build on the existing literature on multiple-discrete choice (see Hendel 1999; Dubé 2005; Gentzkow 2007), and discrete-continuous choice (see Dubin and McFadden 1984; Hanemann 1984; Smith 2004).<sup>8</sup> Our multi-category multi-store model brings together the empirical literature that measures market 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 modeled (e.g., Smith 2004; Davis 2006; and Houde 2012). The paper also relates to an established literature in quantitative marketing studying store choice (e.g., Bell, Ho, and Tang 1998, Fox, Montgomery, and Lodish 2004) and another studying multi-category demand (e.g., Song and Chintagunta 2007, Mehta 2007) by studying these different aspects of demand in a unified multi-store multi-category utility framework.

The rest of the paper is organized as follows. In Section I we discuss relevant features of the market and the data. We discuss the model in Section II and estimation in Section III. We report estimates in Section IV and in Section V we analyze supermarket pricing.

<sup>7</sup> Some papers (e.g., Lal and Matutes 1994, Lal and Rao 1997) use this theoretical framework to study aspects of supermarket pricing (e.g., “Hi-Lo” pricing, advertising of specific product prices, etc.) that we ignore because they are more relevant at a product level rather than the broader category level of analysis we adopt.

<sup>8</sup> These discrete-continuous papers consider a single discrete and a single continuous choice in which zero demand is not allowed. We generalize to allow for multiple continuous choices and we allow for zeros so that the paper is also related to the literature on demand estimation subject to nonnegativity constraints, notably Wales and Woodland (1983) and Kim, Allenby, and Rossi (2002).



## I. The Market and the Data

Supermarkets became widespread in the United States and United Kingdom in the mid-twentieth 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 B of Table 2—Bakery, Drink, Fruit and Vegetables, among others—along with indicative products in each category.<sup>9</sup> Thus, products in the Bakery category are sold by a traditional baker, Drink in a liquor store, Fruit and Vegetables by a greengrocer, and so on. This definition allows us to analyze cross-effects that are internalized by supermarkets but not in a familiar alternative organization of supply.

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 percent) reported a weekly frequency, with 14 percent less frequently and 16 percent 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.

To analyze shopping behavior, we use data from the TNS Superpanel (now run by Kantar), which records the grocery shopping of a representative panel of households in Great Britain. Our sample is for the three-year period October 2002 to September 2005. 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 2 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. In the period of our data, 26,191 households participated in the consumer panel, with an average of 67.6 weeks recorded per household. 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.

In the rest of this section, we discuss the construction of the data used for estimation and provide descriptive statistics. The model is too computationally burdensome to estimate on the full sample of consumer-weeks and we therefore select a subsample for estimation. Furthermore, we want to maintain multiple observations per consumer in order to use the panel structure of the data. We therefore construct a sample comprising a panel of 2,000 consumers and 3 weeks per consumer. We choose the 3 weeks for each consumer in such a way that they are spaced at quarterly (13-week) intervals in order to avoid interdependencies between weeks for a given consumer and we pick different sets of weeks (randomly) for each consumer, which allows us to make use of time-series price variation across the full sample

<sup>9</sup>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 pricing decisions this level. (For more discussion of these points, see CC 2008, Appendix 8.1, paragraphs 10–13.)

TABLE 1—DESCRIPTIVE STATISTICS: DEMOGRAPHIC/CHOICE SET VARIABLES IN ESTIMATION SAMPLE

Panel A. Demographic variables (2,000 consumers)								Mean	SD
Household size								2.77	1.33
Household weekly income (£) per head								226.20	119.04
Panel B. Choice set variables (180,000 consumer-week-stores: 6,000 consumer-weeks $\times$ 30 stores)									
Panel B1. Store characteristics			Stores	Min dist (km)		Size (1,000 sq ft)		Price	
Firm	Type of firm	(share)	Mean	SD	Mean	SD	Mean	SD	Mean
ASDA	Big Four	0.03	6.54	7.88	45.49	14.04			1.01
Morrison	Big Four	0.06	6.41	6.80	33.31	8.78			1.06
Sainsbury's	Big Four	0.13	4.72	5.70	31.81	16.57			1.21
Tesco	Big Four	0.17	3.61	4.56	31.44	22.43			1.10
M&S	Premium	0.03	6.84	7.75	8.76	1.27			1.81
Waitrose	Premium	0.04	6.58	6.36	18.71	8.27			1.39
Aldi	Discounter	0.03	6.76	7.62	8.17	1.67			0.87
Lidl	Discounter	0.02	10.31	10.17	9.83	3.01			0.78
Netto	Discounter	0.02	8.76	9.14	6.70	1.76			0.76
Iceland	Frozen	0.03	4.60	6.18	4.97	1.26			1.12
Others	Small chains	0.39	1.33	1.61	13.14	9.16			1.19
Panel B2. Prices		Bakery	Dairy	Drink	Dry	Fruit	House	Meat	Milk
Mean		1.15	1.21	1.10	1.15	1.30	1.08	1.13	1.13
Standard deviation		0.19	0.17	0.19	0.19	0.23	0.20	0.19	0.07
(within firm)		0.03	0.04	0.03	0.03	0.05	0.03	0.04	0.04

Notes: The unit of observation for the statistics in panel B is the consumer-week-store. There are 180,000 consumer-week-store observations in the choice sets: 6,000 consumer-week choice sets and 30 stores per choice set. Panel B1 presents means across 180,000 consumer-week-stores of (i) a firm indicator, store size, and price (mean across categories within the store); as well as (ii) the mean across 6,000 consumer-weeks of the minimum (across 30 stores) distance to a store operated by the given firm (omitting consumer-weeks where the firm is not in the choice set). In panel B2 the price statistics are for the 180,000 consumer-week-store price observations for each category.

period. Further details of sample construction are given in online Appendix B where we also show that the estimation sample is representative by comparing demographics between our sample, the full TNS sample, and census data.

To obtain consumer choice sets, we match each consumer to stores based on the distance from the consumer's home. We use a store dataset from the Institute for Grocery Distribution (IGD), which includes the postcode of all supermarket outlets in Great Britain. To compute the distance between consumers and stores we use postcode information in the consumer and store data.<sup>10</sup> We assume that the consumer's choice set is made up of the nearest 30 stores to the consumer's home.<sup>11</sup> The fraction of expenditure on store visits outside the nearest 30 is 1.2 percent. 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 postcode. The postcode is known for 70 percent of store choices. When it is not known we

<sup>10</sup>Geographic coordinates for every postcode 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. We locate each consumer at the average coordinates of the residential postcodes in their postal sector (listed in the Postcode Directory).

<sup>11</sup>The store data include all stores operated by supermarket chains. Where a chain operates more than one very small store in any choice set (defined as having a sales area of less than 10,000 square feet), we use only the nearest of these stores to the consumer; this avoids choice sets from filling up quickly with very small stores.

TABLE 2—DESCRIPTIVE STATISTICS: SHOPPING OUTCOMES IN ESTIMATION SAMPLE

<i>Panel A</i>				
A1. Use of stores: share of consumers (shares sum to 1)				Share
One store per week for all three weeks				0.36
One store per week for two of three weeks				0.26
One store per week for one of three weeks				0.20
One store per week for none of three weeks				0.17
A2. Consumer-weeks with >1 store visits				
				Mean      SD
Expenditure share in 1st store by weekly spending (store A)				0.71      0.16
Expenditure share in 2nd store by weekly spending (store B)				0.23      0.13
A3. Share of category spending in 2nd store for cat. from stores (A, B)				
All consumer-weeks				0.04      0.11
Consumer-weeks with >1 store				0.10      0.15
<i>Panel B. Category spending in 1st store for cat. from stores (A, B)</i>				
		Spending (£/wk)		Zeros
Category	Illustrative products	Mean	SD	(share)
Bakery	Bread, cakes, desserts	3.47	3.33	0.09
Dairy	Cheese, yogurt, butter	3.33	3.27	0.17
Drink	Wine, spirits, lager, cola	4.91	8.20	0.31
Dry grocery	Breakfast cereal, confectionery, coffee	5.68	5.24	0.10
Fruit and vegetables	Fruit and vegetables (including frozen)	7.11	6.09	0.06
Household goods	Pet food, detergents, toilet tissues	6.19	6.98	0.21
Meat	Ready meals, cooked meats, fresh beef	10.34	9.00	0.07
Milk	Low fat fresh milk, organic fresh milk	1.17	1.29	0.30
All categories		42.21	27.02	0.00
<i>Panel C. Category choices, consumer-weeks with &gt;1 store</i>				
Top two stores (A, B)		Tesco/ASDA top store for category (1/0)		
		Bakery	Drink	House      Meat
Tesco and discounter		0.80	0.51	0.71      0.66
Tesco and premium		0.65	0.73	0.86      0.55
ASDA and discounter		0.68	0.44	0.59      0.72
ASDA and premium		0.60	0.80	0.89      0.59
Observations: 6,000 consumer-weeks (2,000 consumers × 3 weeks)				

*Notes:* Taylor Nelson Sofres (TNS) Superpanel survey of consumers in Great Britain, October 2002 to September 2005. The statistics are calculated at consumer-week level (i.e., we aggregate expenditures to the week) for the 6,000 consumer-weeks (2,000 consumers and 3 weeks per consumer) used in the estimation sample. Stores A and B referred to in the table are the consumer's first and second stores by overall spending in any week. In panel B the illustrative products in each category are from TNS's list of 269 most granular product classifications; the full list of such products by category is shown in online Appendix A. In panel C the (1/0) dummies take the value 1 if the consumer's top store (by expenditure) for the category is ASDA or Tesco where the figures displayed are averages for multi-stop shoppers whose top two stores (by spending) are as listed in the first column.

assume the consumer goes to a store (in the choice set) operated by the firm they choose.<sup>12</sup>

We compute price indices at firm level rather than store level. This aligns with the policy of firms in the period of the data, which is to set national prices that do

<sup>12</sup>In many cases there is just one candidate store; in cases with more than one we pick one at random, using empirical probability weights that depend on distance and store size. 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 full sample of consumers, for consumers whose store choices are known.



not vary by store location.<sup>13</sup> The existence of this pricing policy is helpful as we can use prices observed in any transaction in a given week to compute each firm's (national) weekly price index. We use the full sample of transactions in the TNS data to compute the price indices. To compute the price indices we aggregate over two hierarchical levels, following standard practice in price index construction (see, for example, Office for National Statistics 2014, ch. 2). At the lower level we compute a price index for a series of narrowly defined product groups, listed in online Appendix A (e.g., shampoo is a product group in the Household category), using quantity from the transactions data to weight 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 weight the lower-level price indices. At both levels the 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. The weights are computed separately for eight demographic types, 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 type level. We normalize the prices so that the price of ASDA in week 1 for each category and demographic type is 1. To obtain category quantities used in estimation we aggregate expenditure to the store-category-week level for each consumer and divide by price.<sup>14</sup> Further details of price index construction are in online Appendix C.

Table 1 presents descriptive demographic and choice set statistics for the estimation sample. Panel A reports demographic characteristics for the 2,000 consumers.<sup>15</sup> Panels B1 and B2 present statistics on the stores in consumer choice sets. The unit of observation for this part of the table is the consumer-week-store: 2,000 consumers, 3 weeks per consumer, and 30 stores per choice set, yielding 180,000 observations. Each consumer-week has a unique choice set because of geographic and time differences. Panel B1 displays store characteristics by firm. We classify the firms into a number of groups. ASDA, Morrisons, Tesco, and Sainsbury's are traditional supermarkets and we refer to them as the Big Four. They operate large stores that stock a wide range of products in all categories. M&S and Waitrose have an emphasis on high quality fresh food, and we refer to these as Premium firms. Aldi, Lidl, and

<sup>13</sup> "Most retailers set their prices uniformly, or mostly uniformly, across their store network [...]. Various other facets of the retail offer, such as promotions, may also be applied uniformly, or mostly uniformly, across a retailers store network" (CC 2008, paragraph 4.98, pp. 498–501).

<sup>14</sup> See online Appendix E for a discussion of conditions that allow aggregation from product to category level.

<sup>15</sup> We use the household income variable to allow price sensitivity to depend on demographics. The TNS data include a rich list of 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 this income variable (for years 2003–2005) on other demographic variables in the EFS that map to those in the TNS survey, namely indicator variables for the number of cars (0, 1, 2,  $\geq 3$ ), adults (1, 2,  $\geq 3$ ), children (0, 1, 2,  $\geq 3$ ), household size (1, 2, ...,  $\geq 6$ ), geographic region in Great Britain (10 regions), social class (6 classes as described in online Appendix C), tenure of residence (dummies for whether the home is privately owned, privately rented, or public housing, structure of residence (detached house, semi-detached/terrace, and apartment)), year, sex of the Household Reference Person (HRP), and age of the HRP ( $\leq 24$ , 25–34, 35–44, 45–54, 55–64,  $\geq 65$ ). We dropped the top and bottom 1 percent household incomes to avoid outliers. The  $R^2$  is 0.51 and the number of observations in the regression is 17,335.

Netto sell a limited range of grocery products at low prices and are referred to as Discounters. One firm (Iceland) emphasizes frozen food but (like all the firms) it sells all eight categories. The remaining firms (combined in the table as Others) are smaller chains that each have a low market share (namely Co-op, Somerfield, and a group of very minor chains). The table reports the distance from the consumer to the nearest store of each firm: consumers tend to have shorter distances to firms that have many stores. Panel B2 presents the price information at category level. Since category prices are normalized to 1 for ASDA in period 1, a mean category price above 1 (e.g., 1.15 for bakery) indicates that for most weeks and firms the price is higher than in ASDA in period 1. The within-firm standard deviation is due to price variation over time after controlling for firm.

Table 2 reports descriptive statistics on shopping outcomes for the estimation sample. The unit of observation for the table is the consumer-week: 2,000 consumers and 3 weeks per consumer. Panel A1 shows that 36 percent of the consumers use one store per week for all three weeks, while 17 percent use multiple stores in all three weeks. The remaining 47 percent of consumers switch in different weeks between using one and multiple stores. When consumers use more than one store in a given week we note two features of the data, presented in Panels A2 and A3, respectively. First, shopping outside the top two stores by spending is minimal (Panel A2). In our model we therefore allow consumers to visit up to two stores per week, and the observed store choices used in estimation are the top two stores by spending. Second, within any individual category, multi-stop shoppers concentrate expenditure in just one store (the identity of which differs by category). Across all consumers (whether one- or multi-stop) the share of category spending in the category's second store is 4 percent (panel A3). Our model therefore makes the simplifying assumption that consumers use only one store per category. Accordingly, observed category demands used in estimation are the purchases made in the consumer's main store for the category from the consumer's top two stores.

Panel B shows that a substantial proportion of consumers have zero expenditure for a given category in a given week. This may be because consumers do not wish to purchase all categories every week or because they buy from nonsupermarket sellers (e.g., doorstep deliveries are sometimes used for milk in Great Britain). In line with this, our model allows for zero expenditures in individual categories.

Panel C illustrates how multi-stop shoppers allocate their spending between firms of different kinds. We consider the three main types of firm introduced in Table 1: Big Four, Discounters, and Premium. We consider the shopping choices of multi-stop shoppers who use, as their top two stores, a Big Four store in combination with (i) a Discounter store or (ii) a Premium store. To represent the Big Four we use ASDA and Tesco, respectively. The table shows the proportion of these shoppers who use these Big Four firms as their main store for the category. Thus, for example, 80 percent of Tesco-Discounter shoppers select Tesco for Bakery, 49 percent of the same group of shoppers select the Discounter for Drink, and so on. A pattern emerges in which the Discounter is strong (relative to the Big Four supermarkets) in categories where products tend to be nonperishable (e.g., Drink and Household goods), but less strong in perishable categories (e.g., Bakery and Meat). The Premium firms have the opposite pattern: relatively strong for perishables and relatively weak for nonperishables.

## II. Utility and Demand

### A. A Simple Multi-Store Multi-Category Model

We start with a simple version of the model to build intuition for the price incentives in the full model. Suppose there are two stores  $A$  and  $B$  and each stocks three categories 1, 2, and 3.<sup>16</sup> A consumer has unit demand for every category, and selects a store for each one. Let the store-category choice  $(A, B, A)$  indicate store  $A$  for 1, store  $B$  for 2, and store  $A$  for 3. There are eight possibilities:  $(A, A, A)$ ,  $(A, A, B)$ ,  $\dots$ ,  $(B, B, B)$ . Let  $p_{jk}$  denote the unit price at store  $j = A, B$  for category  $k = 1, 2, 3$ . The consumer's sensitivity to price is  $\alpha$ .

Suppose utility is additively separable in categories and that a unit of category  $k$  at store  $j$  gives a gross utility  $\mu_{jk}$ . A shopping cost  $\Gamma \geq 0$  is incurred if the consumer visits both stores (two-stop shopping) and avoided if he visits one (one-stop shopping). Thus, for example, choices  $(A, A, A)$  and  $(A, B, A)$  respectively give the following utilities net of price:

$$U(A, A, A) = (\mu_{A1} - \alpha p_{A1}) + (\mu_{A2} - \alpha p_{A2}) + (\mu_{A3} - \alpha p_{A3}) \quad \text{and}$$

$$U(A, B, A) = (\mu_{A1} - \alpha p_{A1}) + (\mu_{B2} - \alpha p_{B2}) + (\mu_{A3} - \alpha p_{A3}) - \Gamma.$$

If the consumer has no shopping cost ( $\Gamma = 0$ ), he selects the store with the highest net utility  $(\mu_{jk} - \alpha p_{jk})$  for each category, independent of the store chosen for the other categories. Alternatively, if his shopping costs are positive ( $\Gamma > 0$ ), his category choices are interdependent, as he may give up the benefit of shopping around to avoid the shopping cost. This interdependence tends to generate complementary effects between categories at the same store: a price increase for one category at the store may induce the consumer to buy *all* categories from the other store.

Consumer tastes—characterized by store-category preferences  $\mu_{jk}$  (for all  $j$  and  $k$ ), price sensitivity  $\alpha$ , and shopping cost  $\Gamma$ —are heterogeneous in the population. Consumers of different  $(\mu, \alpha, \Gamma)$ -type respond to a price increase in different ways, which vary in the extent of the cross-category effects they imply. Consider a price increase at store  $A$  for category 1. Any consumer who initially bought category 1 at store  $A$ , and is marginal in the sense that he stops buying it there after the price increase, can be classified into one of the following four exhaustive response classes:

- (i) Initial one-stop shopper:  $(A, A, A)$ 
  - (a) Drop store  $A$  for all categories: change to  $(B, B, B)$ .
  - (b) Retain  $A$  but drop it for at least category 1: change to  $(B, A, A)$ ,  $(B, B, A)$ , or  $(B, A, B)$ .

<sup>16</sup>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 as a point in a unit square. In this subsection we use  $K = 3$  because one of the consumer responses below, namely (iib), is impossible with  $K = 2$ .

- (ii) Initial two-stop shopper:  $(A, A, B)$  or  $(A, B, B)$  or  $(A, B, A)$ .
  - (a) Drop store  $A$  for all categories: change to  $(B, B, B)$ .
  - (b) Retain store  $A$  but drop it for category 1: change to  $(B, A, B)$  or  $(B, B, A)$ .

Of these four responses, (ia) has the maximal cross-category effect: consumers in this class transfer all three categories from the store. At the other extreme, response (iib) has no cross-category effect. The response class into which a consumer falls depends on his  $(\mu, \alpha, \Gamma)$ -type. Consumers with very high shopping costs  $\Gamma$ , for example, are likely to fall into class (ia) as they strongly prefer to use a single store. Consumers with strong (and varying) store preferences  $\mu_{jk} - \alpha p_{jk}$  by category, on the other hand, are likely to fall into (ib) and (iib) as they are not willing to transfer all their category demands away from store  $A$  even though by doing so they would avoid shopping costs.

We can now relate the model to the two main questions we study in Section V. First, when margins are positive, complementarity between categories has a pro-competitive effect if it is internalized—as is the case in supermarket organization—and the magnitude of this effect depends on the distribution of consumer preferences (e.g., it is greater the larger is the proportion of consumers in class (ia) relative to class (iib)).

Second, we can compare the pro-competitive effects of consumer types that choose one-stop and two-stop shopping respectively by comparing how much each group of shoppers punishes the supermarket for the price increase. We have just seen that, conditional on being marginal (i.e., responding to the price change), initial 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 an individual category (say category 1) between stores  $A$  and  $B$  without incurring shopping costs  $\Gamma$ , 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 shopper group that is marginal.

### B. Full Demand Model

We now specify the full model, which generalizes the number of stores and categories and relaxes the unit demand and additive separability assumptions for categories. We also allow shopping costs to depend on distances to the chosen stores. At a general level one can think of the consumer's weekly problem as choosing how much to purchase in each category at any store. To make the model tractable, based on the data patterns presented in Section I, we assume that consumers visit no more than 2 stores, use only 1 store per category, and only stores that are among the 30 nearest to the consumer (denoted by the set  $\mathcal{J}$ ).<sup>17</sup> In online Appendix D we show

<sup>17</sup>These assumptions can in principle be relaxed in our framework. A relaxation of the second assumption would allow the consumer to select two stores (each with a nonnegative quantity) for each category. This can be

how, based on these restrictions, the utility specification presented below can be derived from a general model of quantity choice under a budget constraint.

We call the one or two stores visited by a consumer his shopping choice, which we denote by  $c$  and write as a set: if  $c$  has two stores  $j$  and  $j'$  then  $c = \{j, j'\}$  and if it has one store  $j$  then  $c = \{j\}$ . Let  $n(c)$  denote the number of stores in  $c$ . The set of available shopping choices  $\mathcal{C}$  comprises all unordered pairs and singletons from the set of available stores  $\mathcal{J}$ . For each shopping choice the consumer has a shopping cost  $\Gamma(c)$ , which depends on the number  $n(c)$  of stores in  $c$  and their locations. Shopping costs include the financial, time, and psychological costs involved in shopping at the stores in  $c$ .

There are  $K$  demand categories, indexed by  $k$ , at each store. For each category the consumer selects a store  $j \in c$ . The store-category choices are summarized in  $\mathbf{d}$ , a vector that lists the store chosen from shopping choice  $c$  for each category. As an illustration, suppose  $K = 3$ , as in Section IIA, and  $c = \{A, B\}$ . Then  $\mathbf{d} = (A, B, A)$  is an example of a store-category choice. We write  $\mathcal{D}_c$  for the set of possible alternatives for  $\mathbf{d}$  given shopping choice  $c$ . For each category the consumer makes a non-negative continuous quantity choice. The quantity choices are given by the  $K \times 1$  vector  $\mathbf{q}$ . Let  $\mathbf{p}$  be the full vector of store-category prices  $p_{jk}$  and  $\boldsymbol{\mu}$  the full vector of store-category tastes  $\mu_{jk}$ .

The consumer's utility from shopping choice  $c$ , store-category choice  $\mathbf{d}$ , and quantity  $\mathbf{q}$ , at prices  $\mathbf{p}$ , is given by

$$(1) \quad U(c, \mathbf{d}, \mathbf{q}, \mathbf{p}) = u(\mathbf{q}, \mathbf{d}) - \alpha \mathbf{p}'_{\mathbf{d}} \mathbf{q} - \Gamma(c) + \varepsilon_c$$

$$(2) \quad = (\boldsymbol{\mu}_{\mathbf{d}} - \alpha \mathbf{p}_{\mathbf{d}})' \mathbf{q} - 0.5 \mathbf{q}' \boldsymbol{\Lambda} \mathbf{q} - \Gamma(c) + \varepsilon_c,$$

where  $u(\mathbf{q}, \mathbf{d}) = \boldsymbol{\mu}'_{\mathbf{d}} \mathbf{q} - 0.5 \mathbf{q}' \boldsymbol{\Lambda} \mathbf{q}$ . The  $K \times 1$  vectors  $\boldsymbol{\mu}_{\mathbf{d}}$  and  $\mathbf{p}_{\mathbf{d}}$  collect the tastes and prices (respectively) that are relevant for each category given store-category choice  $\mathbf{d}$ ;  $\boldsymbol{\Lambda}$  is a symmetric  $K \times K$  matrix of parameters, common across consumers.<sup>18</sup> The first two terms in (1) are variable utility (in terms of  $\mathbf{q}$ ):  $u(\mathbf{q}, \mathbf{d})$  is gross utility from the categories bought, and  $\mathbf{p}'_{\mathbf{d}} \mathbf{q}$  is the consumer's total payment for them. The price sensitivity scalar  $\alpha$  corresponds to the marginal utility of nonsupermarket expenditure (in which utility (1) is quasilinear).

The full model has two sources of product differentiation. First, as in the simple model, there is differentiation between stores at category level, as the consumer views stores differently for any category (captured in the store-category taste vector  $\boldsymbol{\mu}$ ). Second, there is differentiation across shopping choices  $c$  at the level of fixed utility, captured in  $\Gamma(c)$ , which now (unlike the simple model) includes spatial variation in store locations relative to the consumer. A consumer's  $(\boldsymbol{\mu}, \alpha, \Gamma)$ -type fully characterizes his tastes up to  $\varepsilon_c$ , a type-1 extreme value term which is i.i.d. across store choices and which captures any residual unobserved utility that arises from the

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accommodated by extending the quadratic utility specification to allow the number of continuous quantities to be  $2K$  instead of  $K$  when  $n(c) = 2$ , with extra second-order parameters that govern interstore intracategory substitution. This can also be accommodated in the econometric framework in Section III. Given that category spending in the category's second store is low (see Section I) we decided not to generalize in this way.

<sup>18</sup>Unlike many forms (e.g., AIDS), the quadratic is suitable for our purposes as it can naturally accommodate zero demands at category level. Quadratic utility demand is used in Wales and Woodland (1983).

shopping choice. Tastes  $(\boldsymbol{\mu}, \alpha, \Gamma)$  vary in the population of consumers; we specify how in Section IID.

The consumer maximizes  $U(c, \mathbf{d}, \mathbf{q}, \mathbf{p})$  by selecting  $c$ ,  $\mathbf{d}$ , and  $\mathbf{q}$ . The shopping choice  $c$  that gives the highest total utility net of shopping costs is obtained by solving

$$(3) \quad \max_{c \in \mathcal{C}} [w(c, \mathbf{p}) - \Gamma(c) + \varepsilon_c],$$

where

$$(4) \quad w(c, \mathbf{p}) = \max_{\mathbf{d} \in \mathcal{D}_c} \max_{\mathbf{q} \in \mathbb{R}_{\geq 0}^K} [(\boldsymbol{\mu}_{\mathbf{d}} - \alpha \mathbf{p}_{\mathbf{d}})' \mathbf{q} - 0.5 \mathbf{q}' \Lambda \mathbf{q}]$$

is the consumer's indirect variable utility function (i.e., the maximum variable utility from a choice of  $(\mathbf{d}, \mathbf{q})$  given shopping choice  $c$  and prices  $\mathbf{p}$ ).

The outer maximization problem in (4) determines the vector  $\mathbf{d}$  of store-category choices. Note that for any category the consumer always does best to select the store  $j \in c$  with higher linear term in the quadratic equation (2) so that we can write the optimal store-category choices given shopping choice  $c$  and prices  $\mathbf{p}$  as<sup>19</sup>

$$(5) \quad \mathbf{d}(c, \mathbf{p}) = [d_1(c, \mathbf{p}), \dots, d_K(c, \mathbf{p})]$$

$$= [\arg \max_{j \in c} (\mu_{j1} - \alpha p_{j1}), \dots, \arg \max_{j \in c} (\mu_{jK} - \alpha p_{jK})].$$

The inner nested maximization problem in (4) implies a system of  $K$  category demands conditional on store-category choice vector  $\mathbf{d}$ ,

$$(6) \quad \mathbf{q}(\mathbf{d}, \mathbf{p}) = \arg \max_{\mathbf{q} \in \mathbb{R}_{\geq 0}^K} [(\boldsymbol{\mu}_{\mathbf{d}} - \alpha \mathbf{p}_{\mathbf{d}})' \mathbf{q} - 0.5 \mathbf{q}' \Lambda \mathbf{q}],$$

where the consumer may choose a zero demand for any  $k$ . We write the  $k$ th element of  $\mathbf{q}(\mathbf{d}, \mathbf{p})$  as  $q_k(\mathbf{d}, \mathbf{p})$ .

Thus, indirect variable utility (4) is

$$w(c, \mathbf{p}) = (\boldsymbol{\mu}_{\mathbf{d}(c, \mathbf{p})} - \alpha \mathbf{p}_{\mathbf{d}(c, \mathbf{p})})' \mathbf{q}(c, \mathbf{p}) - 0.5 \mathbf{q}(c, \mathbf{p})' \Lambda \mathbf{q}(c, \mathbf{p}),$$

where  $\mathbf{q}(c, \mathbf{p}) = \mathbf{q}(\mathbf{d}(c, \mathbf{p}), \mathbf{p})$ . Expressions (3), (5), and (6) give our model's predictions of consumer behavior.

### C. Cross-Category Effects at Store Level

In this subsection we return to the discussion in IIA of how consumers respond to a price change. To do this we aggregate across shopping choices ( $c$ ) to present the consumer's behavior at store level ( $j$ ), which is the level most relevant for thinking about a store's pricing incentives. (We note that the discussion in this subsection

<sup>19</sup>Optimal  $\mathbf{d}$  is invariant in  $\mathbf{q}$ . This follows by the absence of store-specific effects in  $\Lambda$ .



is useful for understanding the pricing analysis of Section V but does not develop anything that enters our estimator.)

First, consider continuous demand responses conditional on store-category choice  $\mathbf{d}$ . If  $\mathbf{d}$  is such that the consumer chooses store  $j$  for category  $k$ , then the solution to the problem in (6) implies

$$(7) \quad q_k(\mathbf{d}, \mathbf{p}) = \max \left[ \frac{1}{\Lambda_{kk}} \left( \mu_{jk} - \alpha p_{jk} - 0.5 \sum_{k' \neq k} \Lambda_{kk'} q_{k'}(\mathbf{d}, \mathbf{p}) \right), 0 \right].$$

Equation (7) illustrates how category demands respond to price (holding  $\mathbf{d}$  constant). The diagonal second-order quadratic terms, i.e.,  $\Lambda_{kk}$  for any  $k$ , scale demand and (since  $\alpha$  is fixed across categories) allow own-price effects to vary across categories.<sup>20</sup> The off-diagonal second-order terms  $\Lambda_{kk'}$  determine cross-category effects between  $k$  and  $k'$  (a positive value indicates substitutes, a negative value complements).

We now consider the consumer's demand for category  $k$  at the level of store  $j$ . We aggregate over the set  $\mathcal{C}_j$  of shopping choices that include store  $j$ :

$$(8) \quad Q_{jk}(\mathbf{p}) = \sum_{c \in \mathcal{C}_j} \left\{ q_k(\mathbf{d}(c, \mathbf{p}), \mathbf{p}) \times 1[j = d_k(c, \mathbf{p})] \right. \\ \left. \times 1[c = \arg \max_{c' \in \mathcal{C}} (w(c', \mathbf{p}) - \Gamma(c') + \varepsilon_{c'})] \right\}.$$

This expression does not condition on the chosen  $c$  or  $\mathbf{d}$  and hence allows both to change in response to a price change. The right-hand side of (8) therefore allows us to identify three distinct types of consumer response that follow a marginal increase in store  $j$ 's category  $k$  price  $p_{jk}$ : (i) an intensive margin change in the consumer's continuous conditional demand  $q_k$  holding store-category choice  $\mathbf{d}$  constant; (ii) a change in the store-category choice  $d_k$  for category  $k$ , holding shopping choice  $c$  constant; and (iii) a change in shopping choice  $c$ . In the simple example in IIA two of these responses were present: (ii) and (iii). Response (i) is now added because we allow for continuous demands. As was the case in the simple example in IIA, complementary cross-category pricing effects are generated at store  $j$  via demand response (iii): a shopper may switch store for all products because the increase in the price of product  $k$ . In the full model there may be further cross-category effects via response (i) which can be of either sign depending on the off-diagonal second-order quadratic utility parameters  $\Lambda_{kk'}$  in equation (7).

#### D. Specification of Consumer Type Heterogeneity

In this subsection we specify how tastes  $(\boldsymbol{\mu}, \alpha, \Gamma)$  vary across consumers  $i$  and weeks  $t$ . We now introduce consumer and time subscripts.

We begin with consumer  $i$ 's taste at time  $t$  at store  $j$  for category  $k$  which is written in terms of observed and unobserved taste-shifters:

$$(9) \quad \mu_{itjk} = \xi_{jk} + \beta_{0k}(\beta_1 h z_i + \beta_2 s z_j + \mathbf{T}_t \boldsymbol{\beta}_T + \sigma_1 \nu_i^\mu + \sigma_2 \nu_{it}^\mu + \sigma_3 \nu_{ik}^\mu + \sigma_4 \nu_{ijk}^\mu).$$

<sup>20</sup>The specification thus allows the demand elasticity (conditional on store-category choice  $\mathbf{d}$ ) to vary across categories, as the slope and intercept both have a distinct parameter for each category.

The firm category effect  $\xi_{fk}$  is common to all consumers and may vary by firm ( $f$ ) and category ( $k$ ) because different firms do not offer the same branded products, and because many products (e.g., private labels) are firm-specific (see, e.g., Corstjens and Lal 2000). Variation in firm-category strengths was suggested by the data presented in Section I.<sup>21</sup>

The remainder of  $\mu_{ijk}$ , i.e.,  $\beta_{0k}(\beta_1 hz_i + \dots)$ , allows the utility for consumer  $i$  and store  $j$  at time  $t$  to deviate from the firm-category mean  $\xi_{fk}$ . In the interest of parsimony, the parameters (but not all of the random terms) in this component are common across categories, up to a scaling term  $\beta_{0k}$  which allows the size of the effect to vary across categories (to normalize we set  $\beta_{0k} = 1$  for  $k = K$ ). Note that the scaling term allows the variance of the random utility shocks to differ across categories.

The observable variables are: household size  $hz_i$ , which allows continuous demand to be greater for larger households, the log of the store's floor space  $sz_j$  which allows larger stores to offer greater quality (e.g., because of a better selection of products), and quarter and year dummies  $\mathbf{T}_t$ , which allow for seasonal and year effects.<sup>22</sup> The remaining terms in (9) are four random taste components (each i.i.d.  $N(0, 1)$ ): a consumer effect  $\nu_i^\mu$ , a consumer-time effect  $\nu_{it}^\mu$ , a category-specific effect  $\nu_{ik}^\mu$ , and a store-category effect  $\nu_{ijk}^\mu$ . These are scaled by parameters  $(\sigma_1, \dots, \sigma_4)$ . The last of these introduces (horizontal) product differentiation at store-category level, allowing each consumer to view stores differently for any category. Thus, store-category differentiation is partly vertical, reflecting differences in the average quality of stores for any category, and partly horizontal, reflecting variation in individual consumer preferences. Finally note that (i) with the exception of  $\nu_{it}^\mu$  the unobserved heterogeneity through the  $\nu$ -terms in utility are constant across time, capturing permanent unobserved effects and (ii) the first two terms ( $\nu_i^\mu$  and  $\nu_{it}^\mu$ ) are common across categories and hence allow for correlation in the unobserved taste shocks across categories.

The price coefficient  $\alpha_i$  is specified to allow heterogeneity in price sensitivity

$$(10) \quad \alpha_i = (\alpha_1 + \alpha_2/(y_i/hz_i)) \nu_i^\alpha,$$

where  $y_i$  is household  $i$ 's income,  $hz_i$  is household size. The variable  $\nu_i^\alpha$  is a Rayleigh(1) random shock which introduces heterogeneity in a parsimonious way while ensuring positive price sensitivity  $\alpha_i > 0$  for all  $i$ , as long as  $\alpha_1$  and  $\alpha_2$  are positive.

Shopping costs are given by

$$(11) \quad \Gamma_i(c) = (\gamma_{11} + \gamma_{12}\nu_{i1}^\Gamma) 1[n(c)=2] + (\gamma_{21} + \gamma_{22}\nu_{i2}^\Gamma) dist_{ic},$$

<sup>21</sup> The main firms are listed in Table 1. To economize on  $\xi$  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 minor chains). This results in nine firms (or firm groups) that have a distinct  $\xi$  for each  $k$ : ASDA, Morrison, Sainsbury's, Tesco, M&S, Waitrose, Iceland, Discounters, and Others.

<sup>22</sup> The use of a firm dummy with a store size variable to pick up the quality on offer at a store is consistent with the following quotation from CC (2008, paragraph 6.33): "Product range for many retailers is also, in large part, uniform across stores with variations for the most part being a function of store size..."

where  $n(c)$  is the number of stores in  $c$  and  $dist_{ic} = 2 \sum_{j \in c} dist_{ij}$  is the total distance of traveling to each store and back;  $\nu_{i1}^\Gamma$  and  $\nu_{i2}^\Gamma$  are each i.i.d.  $N(0, 1)$ .

The model allows for correlation in unobserved utility between alternative shopping choices  $c$  with stores in common through the  $\nu_{ijk}$  terms that enter (9), as well as through the unobserved components of the shopping cost term (11). The idiosyncratic term ( $\varepsilon_{itc}$ ) in equation (2) is i.i.d. for each  $(i, t, c)$  combination and captures any residual unobserved utility that arises from the shopping choice.<sup>23</sup>

Consumers are observed in our data only if they have positive expenditure in at least one category (see Section II). In theory it is possible for our model to predict that a consumer visits a shopping choice  $c$  but makes zero purchases, for example as a consequence of a high price sensitivity shock  $\nu_i^\alpha$  or a low overall demand shock ( $\nu_i^\mu$  or  $\nu_{it}^\mu$ ). Our model is flexible enough, however, to ensure that this happens only with a negligible probability (0.014 at our parameter estimates), thereby closely matching what is observed in the data.

### III. Estimation and Empirical Strategy

The full set of parameters to be estimated is  $\theta = (\theta^w, \gamma)$ , where  $\theta^w = (\beta, \xi, \sigma, \alpha, \Lambda)$  groups the parameters in variable utility and  $\gamma$  those in shopping costs. In the same way, let  $\mathbf{x}_{itc}^w = (\mathbf{x}_{itj}^w)_{j \in c}$  and  $\boldsymbol{\nu}_{itc}^w = (\nu_i^\mu, \nu_{it}^\mu, \nu_{ik}^\mu, \nu_{ijk}^\mu, \nu_i^\alpha)_{j \in c, k=1, \dots, K}$  be the observables (including prices) and taste shocks in variable utility, and  $(\mathbf{x}_{ic}^\Gamma, \boldsymbol{\nu}_i^\Gamma)$  be the observables and taste shocks (excluding  $\varepsilon_{itc}$ ) entering fixed shopping costs. Finally, we define  $\mathbf{x}_{it} = (\mathbf{x}_{itc}^w, \mathbf{x}_{ic}^\Gamma)_{c \in \mathcal{C}_{it}}$ ,  $\boldsymbol{\nu}_{it} = [(\boldsymbol{\nu}_{itc}^w)_{c \in \mathcal{C}_{it}}, \boldsymbol{\nu}_i^\Gamma]$ , and  $\boldsymbol{\varepsilon}_{it} = (\varepsilon_{itc})_{c \in \mathcal{C}_{it}}$ .

We make use of two core demand expressions in estimation. These are based on  $w(c, \mathbf{p})$ ,  $\mathbf{d}(c, \mathbf{p})$ , and  $\mathbf{q}(\mathbf{d}, \mathbf{p})$ , as given in (4), (5), and (6), now with  $i$  and  $t$  subscripts added to indicate dependence on consumers and time as described in Section IID. The first is the quantity demanded of category  $k$  in store  $j$  (by  $i$  in week  $t$ ) conditional on shopping choice  $c$ :

$$(12) \quad q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w) = q_{itk}(\mathbf{d}_{it}(c, \mathbf{p}_t), \mathbf{p}_t) \times 1[j = d_{itk}(c, \mathbf{p}_t)].$$

Since this conditions on shopping choice, the arguments  $(\theta^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w)$  of this function relate to variable utility but not shopping costs. The second demand expression is the indicator for whether consumer  $i$  in week  $t$  chooses shopping choice  $c$ :

$$(13) \quad I_c(\theta, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}, \boldsymbol{\varepsilon}_{it}) \\ = 1[w_{it}(c, \mathbf{p}_t) - \Gamma_i(c) + \varepsilon_{itc} \geq w_{it}(c', \mathbf{p}_t) - \Gamma_i(c') + \varepsilon_{itc'}, \forall c' \in \mathcal{C}_{it}].$$

<sup>23</sup>The scale of the parameters is determined by normalizing the parameter on the random shopping cost disturbance  $\varepsilon$  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  $(\boldsymbol{\mu}, \alpha, \Lambda)$ , i.e., writing demand as a function of parameters,  $q(\mathbf{d}, \mathbf{p}; \kappa \boldsymbol{\mu}^*, \kappa \alpha^*, \kappa \Lambda^*) = q(\mathbf{d}, \mathbf{p}; \boldsymbol{\mu}^*, \alpha^*, \Lambda^*)$ , where  $(\boldsymbol{\mu}^*, \alpha^*, \Lambda^*)$  represents some arbitrary value. This does not, however, allow another normalization because variable utility (4) is homogeneous of degree one in the same parameters, i.e.,  $w(c, \mathbf{p}; \kappa \boldsymbol{\mu}^*, \kappa \alpha^*, \kappa \Lambda^*) = \kappa w(c, \mathbf{p}; \boldsymbol{\mu}^*, \alpha^*, \Lambda^*)$ , so that their scale  $\kappa$  determines the relative importance of variable utility as compared to shopping costs in the consumer shopping choice problem (3). Since we have not normalized  $(\boldsymbol{\mu}, \alpha, \Lambda)$  we do not need a further parameter to multiply  $w(c, \mathbf{p})$  in (3).

The arguments  $(\theta, \mathbf{x}_{it}, \mathbf{v}_{it}, \epsilon_{it})$  of this function relate to both variable utility and shopping costs.

Two important issues arise when estimating the class of demand model proposed here. First, since consumers self-select into which store to visit, and a common set of parameters and unobservables drive both store and quantity choice, there is a selection issue when estimating quantity choice (12). Second, corner solutions, where a consumer does not have positive demands for all categories, occur often in the data.

We deal with the first issue by simultaneously estimating all the parameters in a framework where store and quantity choices are jointly determined by the combination of (12) and (13). Smith (2004) uses a similar approach in a setting with a single continuous choice. Importantly, in our model, the variables that determine shopping choice are not the same as those that determine quantity choice: distance enters shopping costs but is excluded from variable utility. This exclusion restriction is helpful to identify the parameters in shopping costs separately from those in variable utility.<sup>24</sup>

We address the second issue, zero category demands, by explicitly modeling the nonnegativity constraints in the consumer's category demand problem (6). For each combination of binding and nonbinding constraints, we find the quantities that satisfy the relevant optimality conditions, and then choose the solution that yields the maximum variable utility,  $w_{it}(c, \mathbf{p})$ .<sup>25</sup> As can be seen from (13), to form a prediction of whether  $c$  is chosen, we need to find  $w_{it}(c', \mathbf{p})$  for each  $c' \in \mathcal{C}_{it}$ . In comparison to standard discrete-choice models where the utility of each alternative is a closed-form function of the parameters, the calculation of  $w_{it}(c', \mathbf{p})$  (as the solution to a quadratic programming problem with nonnegativity constraints) adds a new layer of computation that must be carried out for each draw of consumer tastes.<sup>26</sup>

Our approach to the two issues (selection and corner solutions) brings together two strands of demand modeling: (i) the discrete-continuous literature that jointly models a (discrete) store and (continuous) category choice (but does not allow zero category demands), e.g., Dubin and McFadden (1984) and Smith (2004); and (ii) the literature that models nonnegativity constraints explicitly (but does not consider store choices), e.g., Wales and Woodland (1983) and Kim, Allenby, and Rossi (2002).

We estimate the model's parameters using the generalized method of moments (GMM) rather than maximum likelihood.<sup>27</sup> Both methods involve calculating

<sup>24</sup>We also note that distance is a strong predictor of store choice. The literature on selection models (see Moffitt 1999) emphasizes the importance of excluded variables that are strongly correlated with the selection outcome (store choice in our setting) and excluded from the outcome equation (quantity choice). Distance plays the role of such an exclusion restriction on our setting.

<sup>25</sup>For a simple example, if  $K = 2$ , there are  $2^K$  such combinations: (i)  $q_1 > 0, q_2 > 0$ , (ii)  $q_1 > 0, q_2 = 0$ , (iii)  $q_1 = 0, q_2 > 0$ , (iv)  $q_1 = q_2 = 0$ . In each case (i)–(iii), a first-order condition implies a quantity for the nonzero categories, e.g.,  $\mu_1 - \alpha p_1 - \Lambda_{11} q_1 = 0$  for (ii). If these quantities are all positive, this is a candidate solution. The final step is to compare the utilities resulting from these candidate solutions as well as from case (iv). In the general setting where  $K = 8$ , there are  $2^8 = 256$  combinations for each consumer-week/shopping choice/random draw if all  $K$  categories are interacted in utility.

<sup>26</sup>In a standard multinomial logit discrete-choice framework, the choice probability of  $c$  is  $e^{v_c} / \sum_{c'} e^{v_{c'}}$  where utility has a closed form:  $v_c = \mathbf{x}_c \theta$ . In our model, utility depends on a new level of optimization, with no closed-form solution:  $v_c = \Gamma_c + \max_d \max_{q \geq 0} [(\mu_d - \alpha \mathbf{p}_d)' \mathbf{q} - 0.5 \mathbf{q}' \Lambda \mathbf{q}]$ . Thomassen (2009, forthcoming) uses a simpler version of the same structure, where  $v_c = \mu_c + \max_k [x_{ck} \theta]$  and  $x_{ck}$  is horsepower (and price) of engine variant  $k$  of car model  $c$ .

<sup>27</sup>The papers cited in the previous paragraph mostly use a likelihood approach. The likelihood for our model nests the likelihoods in those papers and is derived in online Appendix G.

the probability of the consumer making the observed shopping choice  $c$ , i.e., the expected value of (13). As discussed above, this is computationally demanding because of the presence of corner solutions, and would be prohibitive for more than a small number of draws of  $\nu$  for each consumer. Accordingly, we use the method of simulated moments, which has the advantage of being consistent for a fixed number of draws of  $\nu$  (see McFadden 1989, Pakes and Pollard 1989).

A standard concern is that prices depend on unobserved factors that affect demand. To deal with this possibility, we include fixed effects  $\xi_{fk}$  to control for market-level unobserved quality for each firm-category combination, and time dummies to control for market-level year and quarter effects. We believe this ensures that market-level demand shocks are included in the model, and therefore assume that there is no dependence between price and the unobservables  $\nu$  and  $\epsilon$ .

To construct our estimator, we use (12) and (13) to form conditional expectations of choice outcomes that we observe in the data. (We condition on the explanatory variables  $\mathbf{x}$ , but not on choice variables like shopping choice.) In this paragraph, to bring out the underlying structure shared by all our moment conditions, we let  $Y^*$  denote any choice outcome that we use as a dependent variable, e.g., quantity purchased of  $k$  in  $j$  within  $c$ . (For simplicity we drop subscripts.) For each dependent variable  $Y^*$ , we assume that its value is determined by  $\mathbf{x}$ ,  $\nu$ , and  $\epsilon$  through a known relationship that is given by our structural model evaluated at the true parameter value  $\theta_0$ .<sup>28</sup>

$$(14) \quad Y^* = Y(\theta_0, \mathbf{x}, \nu, \epsilon),$$

$$(15) \quad \nu, \epsilon | \mathbf{x} \sim \text{with known density } f(\nu, \epsilon | \mathbf{x}).$$

In light of the discussion in the previous paragraph, we assume independence between  $(\nu, \epsilon)$  and  $\mathbf{x}$  so that  $f(\nu, \epsilon | \mathbf{x}) = f(\nu, \epsilon)$ .<sup>29</sup> We can write the population conditional expectation in terms of the model's primitives as

$$(16) \quad Y(\theta, \mathbf{x}) = E[Y(\theta, \mathbf{x}, \nu, \epsilon) | \mathbf{x}] = \int \int Y(\theta, \mathbf{x}, \nu, \epsilon) f(\nu, \epsilon | \mathbf{x}) d\epsilon d\nu,$$

so that the following condition, which we use for estimation, holds:<sup>30</sup>

$$(17) \quad E[Y^* - Y(\theta_0, \mathbf{x}) | \mathbf{x}] = 0.$$

As we explain in more detail in subsections IIIA–IIIC, we use moment conditions, all of which are of the type (17), for a number of different dependent variables  $Y^*$ , to

<sup>28</sup>For instance, when  $Y^*$  is the quantity  $Q_{icjk}^*$  purchased of category  $k$  in store  $j$  and in shopping choice  $c$ ,  $Q_{icjk}^* = Q_{cjk}(\theta_0, \mathbf{x}_{it}, \nu_{it}, \epsilon_{it}) = q_{cjk}(\theta_0^w, \mathbf{x}_{it}^w, \nu_{it}^w) I_c(\theta_0, \mathbf{x}_{it}, \nu_{it}, \epsilon_{it})$ .

<sup>29</sup>We note that (14) and (15) are the type of assumptions needed to form a maximum likelihood estimator (MLE). Therefore, our GMM estimator is based on exactly the same structural assumptions that would be used for MLE.

<sup>30</sup>This is an instance of the general fact that  $E[y - E(y|x) | x] = 0$ . To see why this is true here, first note that since  $f(\nu, \epsilon | \mathbf{x})$  is a density,  $\int \int f(\nu, \epsilon | \mathbf{x}) d\epsilon d\nu = 1$ . Then, the left-hand side of (17) can be rewritten, using (14) and (16), as  $Y(\theta_0, \mathbf{x}) - \int \int Y(\theta_0, \mathbf{x}) f(\nu, \epsilon | \mathbf{x}) d\epsilon d\nu = Y(\theta_0, \mathbf{x}) - Y(\theta_0, \mathbf{x}) \int \int f(\nu, \epsilon | \mathbf{x}) d\epsilon d\nu = 0$ .

construct a GMM estimator.<sup>31</sup> For each dependent variable we use a star, as in  $Q_{itcj}^*$ , to indicate both a variable's realization in our sample and the corresponding population variable. To denote the conditional expectation (16) given the explanatory variables, we use the variable's symbol (without a star) and with  $\theta$  and  $\mathbf{x}$  as arguments, e.g.,  $Q_{cjk}(\theta, \mathbf{x}_{it})$ . We also informally discuss the identification of the parameters in IIIA–IIIC. Section IIID details how the moment conditions are combined in the estimator.

### A. Within-Period Moment Conditions

A distinctive feature of our data, compared to many discrete-choice applications, is that choice sets are different for each individual consumer because of location differences. This results in variation in store characteristics and household attributes that is useful for estimating the effects of these variables on choice outcomes. In this subsection we discuss moment conditions that rely primarily on this type of cross-sectional variation, while the next two subsections consider the role of repeated choices by the same consumer.

We start by defining the three dependent variables discussed in this subsection. For each consumer-week  $it$ , let  $Q_{itcj}^*$  be the quantity purchased of category  $k$  in store  $j$  and shopping choice  $c$ ;  $D_{itcj}^*$  equals 1 if this quantity is positive and 0 otherwise, and  $I_{itc}^*$  equals 1 if  $c$  is chosen and 0 otherwise. (For instance, if  $i$  in  $t$  visits  $j$  and no other store, then  $Q_{itcj}^* = D_{itcj}^* = I_{itc}^* = 0$  for all  $c \neq \{j\}$ .)

Before defining the conditional expectation functions (16) for the three dependent variables, we note that the conditional expectation of (13) given  $(\mathbf{x}_{it}, \nu_{it})$  can be written as

$$(18) \quad \begin{aligned} P_c(\theta, \mathbf{x}_{it}, \nu_{it}) &= \int I_c(\theta, \mathbf{x}_{it}, \nu_{it}, \varepsilon_{it}) f(\varepsilon_{it}) d\varepsilon_{it} \\ &= \frac{\exp[w_{it}(c, \mathbf{p}_t) - \Gamma_i(c)]}{\sum_{c' \in \mathcal{C}_{it}} \exp[w_{it}(c', \mathbf{p}_t) - \Gamma_i(c')]} \end{aligned}$$

by the assumption that  $\varepsilon_{itc}$  is i.i.d. type-1 extreme value for each  $c$  and independent of  $\nu_{it}$ . We can now write the conditional expectation functions as<sup>32</sup>

$$(19) \quad Q_{cjk}(\theta, \mathbf{x}_{it}) = \int q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \nu_{itc}^w) P_c(\theta, \mathbf{x}_{it}, \nu_{it}) f(\nu_{it}) d\nu_{it},$$

$$(20) \quad D_{cjk}(\theta, \mathbf{x}_{it}) = \int 1[q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \nu_{itc}^w) > 0] P_c(\theta, \mathbf{x}_{it}, \nu_{it}) f(\nu_{it}) d\nu_{it},$$

$$(21) \quad I_c(\theta, \mathbf{x}_{it}) = \int P_c(\theta, \mathbf{x}_{it}, \nu_{it}) f(\nu_{it}) d\nu_{it}.$$

<sup>31</sup> These are the conditional moment restrictions (22)–(24) and the unconditional moment restrictions (32)–(36) and (41)–(42).

<sup>32</sup> To see this for (19):  $Q_{cjk}(\theta, \mathbf{x}_{it}) = \int \int q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \nu_{itc}^w) I_c(\theta, \mathbf{x}_{it}, \nu_{it}, \varepsilon_{it}) f(\nu_{it}) f(\varepsilon_{it}) d\varepsilon_{it} d\nu_{it} = \int q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \nu_{itc}^w) \left[ \int I_c(\theta, \mathbf{x}_{it}, \nu_{it}, \varepsilon_{it}) f(\varepsilon_{it}) d\varepsilon_{it} \right] f(\nu_{it}) d\nu_{it} = \int q_{cjk}(\theta^w, \mathbf{x}_{itc}^w, \nu_{itc}^w) P_c(\theta, \mathbf{x}_{it}, \nu_{it}) f(\nu_{it}) d\nu_{it}.$



The conditions (17) are now

$$(22) \quad E[Q_{itcj}^* - Q_{cjk}(\boldsymbol{\theta}_0, \mathbf{x}_{it}) | \mathbf{x}_{it}] = 0, \text{ for } k = 1, \dots, K,$$

$$(23) \quad E[D_{itcj}^* - D_{cjk}(\boldsymbol{\theta}_0, \mathbf{x}_{it}) | \mathbf{x}_{it}] = 0, \text{ for } k = 1, \dots, K,$$

$$(24) \quad E[I_{itc}^* - I_c(\boldsymbol{\theta}_0, \mathbf{x}_{it}) | \mathbf{x}_{it}] = 0.$$

Expressions (22)–(24) imply orthogonality conditions (between the prediction errors and functions of the explanatory variables) that we use, by the analogy principle, to form the following empirical moments (that our estimator seeks to bring as close to zero as possible in the sample):

$$(25) \quad \mathbf{g}_i^{(1)}(\boldsymbol{\theta}) = \begin{bmatrix} \sum_{t=1}^T \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} \mathbf{Z}_{itcj}^Q (Q_{itcj1}^* - Q_{cj1}(\boldsymbol{\theta}, \mathbf{x}_{it})) \\ \vdots \\ \sum_{t=1}^T \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} \mathbf{Z}_{itcj}^Q (Q_{itcjK}^* - Q_{cjK}(\boldsymbol{\theta}, \mathbf{x}_{it})) \\ \sum_{t=1}^T \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} \mathbf{Z}_{itcj}^D (D_{itcj1}^* - D_{cj1}(\boldsymbol{\theta}, \mathbf{x}_{it})) \\ \vdots \\ \sum_{t=1}^T \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} \mathbf{Z}_{itcj}^D (D_{itcjK}^* - D_{cjK}(\boldsymbol{\theta}, \mathbf{x}_{it})) \\ \sum_{t=1}^T \sum_{c \in \mathcal{C}_{it}} \mathbf{Z}_{itc}^I (I_{itc}^* - I_c(\boldsymbol{\theta}, \mathbf{x}_{it})) \end{bmatrix}.$$

Here (and elsewhere, unless stated otherwise) the subscript  $t$  refers to the  $t$ th time period (week) in the sample for consumer  $i$ . (As noted in Section I, we draw three weeks at quarterly intervals for each consumer (so that  $T = 3$ ) where the weeks differ across consumers.) The vectors  $\mathbf{Z}_{itcj}^Q$ ,  $\mathbf{Z}_{itcj}^D$ , and  $\mathbf{Z}_{itc}^I$  are functions of the explanatory variables  $\mathbf{x}_{it}$ . We now discuss their components (which are also listed in online Appendix F) and explain informally how they help with the estimation of the parameters. Parameters can be grouped according to whether they are in  $\boldsymbol{\mu}$ ,  $\boldsymbol{\alpha}$ ,  $\boldsymbol{\Lambda}$ , or  $\boldsymbol{\gamma}$ . We discuss them in this order. We leave discussion of the spread parameters for unobserved heterogeneity until the next two subsections.

Consider first the parameters in  $\boldsymbol{\mu}$ . The vectors  $\mathbf{Z}_{itcj}^Q$  and  $\mathbf{Z}_{itcj}^D$  contain log of store size, household size, eight firm dummies, and a constant. The moments involving these variables are particularly useful for estimating the parameters  $\beta_1$ ,  $\beta_2$ , and the firm-category fixed effects  $\xi_{fk}$ . Since these moments are category specific, they also contribute to the identification of the category-specific scaling terms  $\beta_{0k}$  (normalized to 1 for  $k = K$ ). The vector  $\mathbf{Z}_{itcj}^Q$  also includes quarter and year time dummies, which help with the estimation of  $\beta_T$ .

Next consider the parameters in  $\boldsymbol{\alpha}$  and  $\boldsymbol{\Lambda}$ , all of which relate to price effects. To estimate these parameters we include prices in all three moments:  $\mathbf{Z}_{itcj}^Q$  and  $\mathbf{Z}_{itcj}^D$  contain the price of category  $k$  at store  $j$  and the price for each of the other categories  $k'$  with which  $k$  has an interaction term  $\Lambda_{kk'}$ .<sup>33</sup> In  $\mathbf{Z}_{itc}^I$  we include the average of the store-category prices in  $c$ , i.e.,  $\sum_{j \in c} \sum_k p_{jk} / (n(c)K)$ , and the same average divided by the per-capita household income of consumer  $i$ . The same-category (diagonal)

<sup>33</sup>When  $n(c) = 1$  we use the price of  $k'$  in store  $j$  and when  $n(c) = 2$  we use the average price of  $k'$  in the two stores in  $c$ .

terms  $\Lambda_{kk}$  and the price parameters  $\alpha_1, \alpha_2$  all affect the overall price response, and to estimate them we exploit the fact that we observe price effects both at the quantity and store-choice levels:  $\Lambda_{kk}$  is estimated by observing how much less consumers buy of  $k$  when its price changes, whereas  $\alpha_1$  and  $\alpha_2$  are estimated by observing how much less likely consumers are to visit a store when its prices change.<sup>34</sup>

Now consider the cross-category terms  $\Lambda_{kk'}$ . Here the price of  $k'$  is useful. Gentzkow (2007) discusses the challenge of separately identifying correlation in tastes and cross-category effects (complementarity or substitutability). In our setting cross-category effects in variable utility are driven by the cross-category terms  $\Lambda_{kk'}$ .<sup>35</sup> By contrast, correlation in the taste for categories is determined by the variance of the overall spending shocks  $\sigma_1 \nu_i^\mu + \sigma_2 \nu_{it}^\mu$ . Observing that consumers tend to demand either a lot of both  $k$  and  $k'$  or little of both is consistent with complementarity as well as correlation in tastes. A shock to the price of  $k'$  is a natural experiment that allows us to distinguish between these two possibilities: if correlation between demand for  $k$  and demand for  $k'$  is due entirely to correlation in unobservable tastes (large  $\sigma_1, \sigma_2$ ), the price shock to  $k'$  should have no effect on the demand for  $k$  (since  $k'$  is in this case excluded from the utility of  $k$ ). On the other hand, if there is complementarity ( $\Lambda_{kk'} < 0$ ), a positive price shock to  $k'$  will reduce demand for both  $k'$  and  $k$ .

Finally, with a view to estimating the mean shopping cost parameters  $(\gamma_{11}, \gamma_{21})$ ,  $\mathbf{Z}_{itc}^I$  contains the observable variables in the shopping cost term (11): a dummy for whether  $c$  is a two-store shopping choice (this is also included in  $\mathbf{Z}_{itcj}^O$  and  $\mathbf{Z}_{itcj}^D$ ), and the total distance of traveling to each store and back. To further help with identification of shopping costs we also include distance squared and the interaction of distance and the two-store dummy.

### B. Cross-Period Moment Conditions

We use the panel aspect of the data to estimate the spread parameters on taste shocks that are constant across time. Akerberg et al. (2007) discuss how first- and second-choice data (like in Berry, Levinsohn, and Pakes 2004) or repeated purchases by the same consumer (like in our data) help to pin down the effects of unobserved and observed sources of taste heterogeneity, since both drive correlation between choices, and cross-sectional data alone are sufficient to estimate the latter.<sup>36</sup> Each of the taste shocks in our model influences one observed outcome in particular, such as total spending, store used, or distance traveled. By matching the observed covariance of each such outcome across time periods, in the same way that Berry,

<sup>34</sup>We see from (7)—i.e.,  $q_k = (\mu_k - \alpha p_k)/\Lambda_{kk}$  (supposing  $q_k > 0$  and  $\Lambda_{kk'} = 0$ )—that  $1/\Lambda_{kk}$  scales category- $k$  demand. Since  $\alpha$  is common to all categories,  $\Lambda_{kk}$  determines a  $k$ -specific price effect for given  $\alpha_1$  and  $\alpha_2$ . Still,  $\alpha_1$  and  $\alpha_2$  determine the scale of variable utility  $(\mu - \alpha \mathbf{p}) \mathbf{q} - 0.5 \mathbf{q}' \Lambda \mathbf{q}$ , relative to shopping costs,  $\Gamma$  (see the discussion in footnote 23), and are therefore identified by the changes in shopping choice associated with variation in the price levels across alternatives  $c$ .

<sup>35</sup>The cost of visiting multiple stores induces cross-category correlation in demands within a store, but this effect is separately identified since distance and  $n(c)$  are observed and excluded from category utility.

<sup>36</sup>“...the correlation between the  $x$ -intensity of the first choice and the second choice of a given individual is a function of both  $\theta^o$  [parameter on unobserved heterogeneity] and the  $\theta^u$  [parameter on observed heterogeneity] terms, and the  $\theta^o$  terms should be able to be estimated from only the first choice data. A similar comment can be made for repeated choices, at least provided the utility function of the consuming unit does not change from choice to choice.” (Akerberg et al. 2007, p. 4193). Comments in square brackets added.

Levinsohn, and Pakes (2004, pp. 74–75) “matched... the covariances between the first-choice product characteristics and the second-choice product characteristics,” we can pin down the parameter for the relevant shock.

Concretely, after taking the conditional expectation given  $(\mathbf{x}_{it}, \boldsymbol{\nu}_{it})$ , overall spending, category-specific quantities, usage incidence of a given store  $j$  for category  $k$ , one-stop shopping, and total distance traveled are

$$(26) \quad r(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} \sum_{k=1}^K p_{ijk} q_{cjk}(\boldsymbol{\theta}^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w) P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}),$$

$$(27) \quad q_k(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} q_{cjk}(\boldsymbol{\theta}^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w) P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}),$$

$$(28) \quad d_{jk}(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{ij}} 1[q_{cjk}(\boldsymbol{\theta}^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w) > 0] P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}),$$

$$(29) \quad os(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{it}} 1[n(c) = 1] P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}),$$

$$(30) \quad dist(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{it}} dist_{ic} P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}),$$

where  $\mathcal{C}_{ij}$  in (28) is the set of shopping choices that include store  $j$  for consumer  $i$  in period  $t$ , and  $p_{ijk}$  is the price of category  $k$  at store  $j$  and time  $t$ . The conditional expectation, given  $(\mathbf{x}_{it}, \mathbf{x}_{i(t-1)})$ , of the product of the respective quantities in adjacent time periods is

$$(31) \quad R(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)}) = \int r(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) r(\boldsymbol{\theta}, \mathbf{x}_{i(t-1)}, \boldsymbol{\nu}_{i(t-1)}) f(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)}) d(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)}),$$

and similarly for (27)–(30). For simplicity we now let  $f$  denote the joint density of  $(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)})$ . Like above, we use a star, e.g.,  $R_{it}^*$ , to indicate a given variable before taking expectations (with respect to any unobservable). By the logic set out above, the equivalent of (17) holds for  $R_{it}^*$  etc. This implies the following unconditional moment conditions:<sup>37</sup>

$$(32) \quad E[R_{it}^* - R(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0,$$

$$(33) \quad E[Q_{itk}^* - Q_k(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0,$$

$$(34) \quad E[D_{itjk}^* - D_{jk}(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0,$$

$$(35) \quad E[OS_{it}^* - OS(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0,$$

$$(36) \quad E[DIST_{it}^* - DIST(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0.$$

Consider first condition (32), which concerns the product of overall spending in adjacent time periods. This condition helps to identify the parameter of the shock  $\sigma_1 \nu_i^\mu$

<sup>37</sup>To see this:  $E[R_{it}^* - R(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = E\{E[R_{it}^* - R(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)}) | \mathbf{x}_{it}, \mathbf{x}_{i(t-1)}]\} = E\{0\} = 0$ .

that is consumer-specific but fixed across time periods  $t$ , categories  $k$ , and stores  $j$ . A large value of  $\sigma_1$  implies that some consumers tend to spend more in all time periods, whereas others tend to spend less in all time periods. Matching this covariance pins down the value of  $\sigma_1$ .

In the same way, we estimate the spread parameters on the category-specific ( $\sigma_3$ ) and store-category-specific ( $\sigma_4$ ) random shocks by matching the covariance between time periods of (non-store-specific) category quantities and of store-category purchase indicators, respectively, as required by (33) and (34). Concretely, the correlation in quantity purchased of  $k$  across periods reveals  $\sigma_3$  and the extent to which consumers tend to use the same store for  $k$  across time periods reveals  $\sigma_4$ . The spread parameters on unobserved heterogeneity in shopping cost ( $\gamma_{12}$ ) and distance traveled ( $\gamma_{22}$ ) are identified by matching the observed and predicted covariances (between adjacent time periods) of one-stop shopping and distance traveled, respectively.

The empirical moments are

$$(37) \quad \mathbf{g}_i^{(2)}(\boldsymbol{\theta}) = \begin{bmatrix} \sum_{t=2}^T (R_{it}^* - R(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \\ \sum_{t=2}^T \sum_{k=1}^K (Q_{itk}^* - Q_k(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \\ \sum_{t=2}^T \sum_{j \in \mathcal{J}_{it,(t-1)}} \sum_{k=1}^K (D_{itjk}^* - D_{jk}(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \\ \sum_{t=2}^T (OS_{it}^* - OS(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \\ \sum_{t=2}^T (DIST_{it}^* - DIST(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \end{bmatrix},$$

where  $\mathcal{J}_{it,(t-1)} = \mathcal{J}_{it} \cap \mathcal{J}_{i(t-1)}$  is the set of stores that are in  $i$ 's choice set in both period  $t$  and period  $t - 1$ .

### C. Cross-Category Moment Conditions

We use cross-category moment conditions to distinguish between the time-invariant shock (with spread parameter  $\sigma_1$ ) and the time-varying shock (with spread parameter  $\sigma_2$ ). Both types of shock impact all categories. However, the time-varying shock generates correlation between spending on  $k$  and  $k'$  in the same period, but—contrary to the time-invariant shock—not between  $k$  in one period and  $k'$  in another period (see Gentzkow 2007 for a related argument). We therefore use separate moment conditions for within-period and cross-period covariances in spending across categories. Spending on category  $k$ , after taking the conditional expectation given  $(\mathbf{x}_{it}, \boldsymbol{\nu}_{it})$ , is

$$(38) \quad r_k(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) = \sum_{c \in \mathcal{C}_{it}} \sum_{j \in c} p_{ijk} q_{cjk}(\boldsymbol{\theta}^w, \mathbf{x}_{itc}^w, \boldsymbol{\nu}_{itc}^w) P_c(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}).$$

We use this to define the following conditional expectations given  $(\mathbf{x}_{it}, \mathbf{x}_{i(t-1)})$  for the average product between spending on  $k$  and  $k'$  within (*in*) and across (*cr*) adjacent time periods,

$$(39) \quad R_{kk'}^{in}(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)}) = \int \frac{1}{2} [r_k(\boldsymbol{\theta}, \mathbf{x}_{i(t-1)}, \boldsymbol{\nu}_{i(t-1)}) r_{k'}(\boldsymbol{\theta}, \mathbf{x}_{i(t-1)}, \boldsymbol{\nu}_{i(t-1)}) \\ + r_k(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) r_{k'}(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it})] f(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)}) d(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)})$$

and

$$\begin{aligned}
 (40) \quad R_{kk'}^{cr}(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)}) \\
 = \int \frac{1}{2} [r_k(\boldsymbol{\theta}, \mathbf{x}_{i(t-1)}, \boldsymbol{\nu}_{i(t-1)}) r_{k'}(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) \\
 + r_k(\boldsymbol{\theta}, \mathbf{x}_{it}, \boldsymbol{\nu}_{it}) r_{k'}(\boldsymbol{\theta}, \mathbf{x}_{i(t-1)}, \boldsymbol{\nu}_{i(t-1)})] f(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)}) d(\boldsymbol{\nu}_{it}, \boldsymbol{\nu}_{i(t-1)}).
 \end{aligned}$$

The unconditional versions of (17) are

$$(41) \quad E[R_{itkk'}^{in*} - R_{kk'}^{in}(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0, \text{ for } k < k',$$

$$(42) \quad E[R_{itkk'}^{cr*} - R_{kk'}^{cr}(\boldsymbol{\theta}_0, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})] = 0, \text{ for } k < k',$$

where, in the same way as above, the star indicates the respective quantities ((39) and (40)) before taking expectations (with respect to any unobservables). We use (41) and (42) to form the following empirical moments:

$$(43) \quad \mathbf{g}_i^{(3)}(\boldsymbol{\theta}) = \begin{bmatrix} \sum_{t=2}^T \sum_{k=1}^K \sum_{k'=k+1}^K (R_{itkk'}^{in*} - R_{kk'}^{in}(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \\ \sum_{t=2}^T \sum_{k=1}^K \sum_{k'=k+1}^K (R_{itkk'}^{cr*} - R_{kk'}^{cr}(\boldsymbol{\theta}, \mathbf{x}_{it}, \mathbf{x}_{i(t-1)})) \end{bmatrix}.$$

#### D. Estimation

To estimate the parameters we write  $\mathbf{g}(\boldsymbol{\theta}) = N^{-1} \sum_{i=1}^N \mathbf{g}_i(\boldsymbol{\theta})$ , where  $\mathbf{g}_i(\boldsymbol{\theta})$  vertically stacks the three sets of moments  $\mathbf{g}_i^{(1)}(\boldsymbol{\theta})$ ,  $\mathbf{g}_i^{(2)}(\boldsymbol{\theta})$ , and  $\mathbf{g}_i^{(3)}(\boldsymbol{\theta})$ . The GMM estimator is

$$(44) \quad \hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \mathbf{g}(\boldsymbol{\theta})' \mathbf{W}^{-1} \mathbf{g}(\boldsymbol{\theta}),$$

where the weighting matrix is the inverse of the covariance matrix  $\mathbf{W} = N^{-1} \sum_{i=1}^N \mathbf{g}_i(\boldsymbol{\theta}) \mathbf{g}_i(\boldsymbol{\theta})'$  and  $\tilde{\boldsymbol{\theta}}$  are first-stage estimates.<sup>38</sup>

#### IV. Estimates and Model Fit

In this section we discuss parameter estimates and model fit. We present estimates for two specifications in Table 3. As a starting point, Model 1 assumes independence between product categories in variable utility, so that the cross-category terms  $\Lambda_{kk'}$  are set to zero. Model 2 relaxes this assumption.

Panel A shows the parameters that enter the store-category taste effects  $\mu_{itjk}$  as specified in equation (9). The effect of household and store size have intuitive

<sup>38</sup>We first obtain preliminary estimates by using only the moments  $\mathbf{g}_i^{(1)}$ , with the inverse of the covariance of the  $\mathbf{Z}$  vectors as the weighting matrix. Then  $(N^{-1} \sum_{i=1}^N \mathbf{g}_i \mathbf{g}_i')^{-1}$  evaluated at these preliminary estimates is the weighting matrix used to obtain the first-stage estimates  $\tilde{\boldsymbol{\theta}}$ . We use a simple frequency simulator with one draw per observation (consumer) and a standard estimator for the asymptotic variance of  $\tilde{\boldsymbol{\theta}}$  (see Wooldridge 2010, p. 527, eq. 14.14). To correct for simulation noise we multiply this variance by a factor of  $1 + \frac{1}{r} = 2$ , where  $r = 1$  is the number of simulation draws per observation (see McFadden 1989, p. 1006).

TABLE 3—ESTIMATED PARAMETERS

		Model 1		Model 2	
		Estimate	SE	Estimate	SE
<i>Panel A. Store-category taste effects (<math>\beta</math>) and scaling terms (<math>\sigma</math>)</i>					
Bakery	$\beta_{01}$	2.374	0.074	2.085	0.037
Dairy	$\beta_{02}$	1.643	0.032	1.418	0.106
Drink	$\beta_{03}$	0.943	0.016	1.096	0.013
Dry grocery	$\beta_{04}$	2.063	0.067	1.901	0.105
Fruit and vegetables	$\beta_{05}$	2.968	0.100	2.665	0.192
Household goods	$\beta_{06}$	1.252	0.022	1.115	0.028
Meat	$\beta_{07}$	2.733	0.128	2.309	0.135
ln(floor space)	$\beta_1$	0.425	0.005	0.456	0.006
Household size	$\beta_2$	0.383	0.008	0.477	0.024
Fixed across category/store	$\sigma_1$	0.197	0.024	0.208	0.012
Time-varying	$\sigma_2$	0.790	0.019	0.920	0.046
Category specific	$\sigma_3$	0.748	0.017	0.677	0.023
Store/category specific	$\sigma_4$	1.033	0.019	1.129	0.015
<i>Panel B. Second-order quadratic parameters (<math>\Lambda</math>)</i>					
Bakery	$\Lambda_{11}$	22.209	1.127	19.852	2.090
Dairy	$\Lambda_{22}$	12.308	0.383	11.239	1.404
Drink	$\Lambda_{33}$	3.261	0.173	3.802	0.192
Dry grocery	$\Lambda_{44}$	11.332	0.582	10.536	0.916
Fruit and vegetables	$\Lambda_{55}$	16.113	0.739	15.952	2.138
Household goods	$\Lambda_{66}$	4.387	0.163	4.360	0.219
Meat	$\Lambda_{77}$	9.882	0.613	8.901	0.883
Milk	$\Lambda_{88}$	14.081	0.330	14.062	1.257
Drink–dry grocery	$\Lambda_{34}$			1.742	0.163
Dairy–milk	$\Lambda_{28}$			1.368	0.555
Bakery–fruit and vegetables	$\Lambda_{15}$			0.269	0.890
Bakery–meat	$\Lambda_{17}$			0.572	0.363
Fruit and vegetables–meat	$\Lambda_{57}$			0.076	0.926
<i>Panel C. Price parameters (<math>\alpha</math>)</i>					
Constant	$\alpha_1$	1.936	0.047	1.839	0.037
1/[weekly income (£) per head]	$\alpha_2$	18.345	3.046	32.881	3.702
<i>Panel D. Shopping costs (<math>\gamma</math>)</i>					
Two store dummy	$\gamma_{11}$	9.665	1.385	7.528	0.917
Standard deviation	$\gamma_{12}$	14.375	2.553	10.269	1.657
Distance	$\gamma_{21}$	0.430	0.026	0.440	0.027
Standard deviation	$\gamma_{22}$	0.396	0.030	0.394	0.028

*Notes:* Parameters are estimated using 6,000 consumer-week observations. Standard errors are corrected for simulation noise. Year, quarter, and firm-category effects not reported.

signs:  $\beta_1$  and  $\beta_2$  are both positive. The spread parameters ( $\sigma_1, \dots, \sigma_4$ ) are precisely estimated. Panel B reports the parameters in the matrix  $\Lambda$  of second-order terms in quadratic utility. The diagonal parameters  $\Lambda_{kk}$  are all positive so that own-price effects are negative. The off-diagonal parameters  $\Lambda_{kk'}$  (in Model 2) are also positive, which implies that categories are intrinsic substitutes (i.e., substitutes in terms of the variable utility function), but the estimated parameters are small and insignificant for three of the five parameters. In the interest of parsimony we estimate only the interaction parameters that we believed a priori to be the most important. (In Section VF we discuss results from a model with alternative interactions and we find that our main results are robust to this alternative). The parameters in the price sensitivity coefficient (10), reported in panel C, are of the expected sign:  $\alpha_1$  and  $\alpha_2$  are positive so that consumers prefer lower prices and price sensitivity is decreasing in



per capita household income. Finally, panel D reports the parameters  $\gamma$  that enter the consumer's shopping costs  $\Gamma(c)$ . The mean and spread parameters for both shopping cost variables are precisely estimated.

Model 1 is a restricted version of Model 2, in which the five off-diagonal elements of  $\Lambda$  are all set to zero. We reject this restriction at a significance level of less than 1 percent. (The  $\chi^2_5$ -distributed GMM distance statistic comparing Model 1 and Model 2 is 19.2.) We use Model 2 as the baseline model for the results in Section VI. In the rest of this section we discuss the fit of this model.

The 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 these choice predictions accurately. For example, firm-specific taste parameters appear only in variable utility (entering as firm-category effects  $\xi_{fk}$ ) and they serve the joint 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 on the estimation sample of 6,000 consumer-weeks, we consider the out-of-sample fit on a validation sample of 6,000 consumer-weeks (with new random taste draws).

We begin at the category level. To check the fit of both demand intensity and demand incidence we consider a continuous and a discrete measure of category demand. The continuous prediction at the firm category level, given estimated parameters  $\hat{\theta}$ , is the total quantity of category  $k$  sold by the firm, i.e.,

$$(45) \quad Q_{fk}(\mathbf{p}) = \sum_{i=1}^N \sum_{t=1}^T \sum_{j \in \mathcal{J}_f} \sum_{c \in \mathcal{C}_{ij}} Q_{cjk}(\hat{\theta}, \mathbf{x}_{it}),$$

where  $Q_{cjk}(\hat{\theta}, \mathbf{x}_{it})$  is  $i$ 's category demand at store  $j$  in shopping choice  $c$  defined in (19). The innermost sum is over the set  $\mathcal{C}_{ij}$  of shopping choices  $c$  that include store  $j$ ;  $\mathcal{J}_f$  is the set of stores owned by firm  $f$ . The discrete demand measure, which we refer to as the number of shoppers, is the total number of consumers who buy a positive quantity of category  $k$  from firm  $f$ , i.e.,

$$(46) \quad D_{fk}(\mathbf{p}) = \sum_{i=1}^N \sum_{t=1}^T \sum_{j \in \mathcal{J}_f} \sum_{c \in \mathcal{C}_{ij}} D_{cjk}(\hat{\theta}, \mathbf{x}_{it}),$$

where  $D_{cjk}(\hat{\theta}, \mathbf{x}_{it})$  is the probability consumer  $i$  buys a positive quantity of  $k$  in store  $j$  in shopping choice  $c$ , defined in (20).

Panel A of Table 4 presents correlation coefficients which show that the predicted and observed firm-category demands from the model are highly correlated. This is also true for the out-of-sample predictions. A high correlation is found both for the discrete and the continuous demand measures.

Panel B of Table 4 checks how close the observed and predicted demands are to each other. In B1 we consider how well the model predicts each firm  $f$ 's share of category  $k$ , written  $s_{fk}$ , in terms of quantities ( $Q_{fk}(\mathbf{p})/\sum_{f'} Q_{f'k}(\mathbf{p})$ ) and shoppers ( $D_{fk}(\mathbf{p})/\sum_{f'} D_{f'k}(\mathbf{p})$ ). The absolute prediction error is the magnitude of the difference between the predicted and observed shares. There are 72 such prediction

TABLE 4—IN-SAMPLE AND OUT-OF-SAMPLE FIT

	In-sample		Out-of-sample					
	Quantity	Shoppers	Quantity	Shoppers				
<i>Panel A. Correlation between predicted and observed demands</i>								
$\rho(Q_{jk}, Q_{jk}^*), \rho(D_{jk}, D_{jk}^*)$	0.994	0.994	0.986	0.991				
<i>Panel B. Mean absolute prediction errors</i>								
B1. Firm share of category demand (all firms and categories)								
$ s_{jk} - s_{jk}^* $	0.008	0.008	0.011	0.009				
B2. 1-stop shopper share of category demand (all categories)								
$ s_{1ss,k} - s_{1ss,k}^* $	0.004	0.020	0.007	0.028				
<i>Panel C. Firm market shares</i>								
	In-sample				Out-of-sample			
	Revenue		Shoppers		Revenue		Shoppers	
	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs
ASDA	0.209	0.214	0.180	0.170	0.204	0.230	0.177	0.176
Morr	0.128	0.113	0.115	0.096	0.134	0.111	0.117	0.092
Sains	0.159	0.153	0.127	0.127	0.157	0.152	0.128	0.123
Tesco	0.327	0.329	0.266	0.256	0.315	0.317	0.256	0.255
M&S	0.005	0.011	0.009	0.026	0.007	0.012	0.010	0.029
Wait	0.021	0.016	0.019	0.020	0.017	0.018	0.017	0.021
Icel	0.008	0.015	0.026	0.036	0.012	0.017	0.030	0.035
Disc	0.025	0.029	0.052	0.055	0.031	0.028	0.056	0.053
Other	0.118	0.120	0.207	0.214	0.123	0.115	0.210	0.216

*Notes:* In-sample predictions use the estimation sample of 6,000 consumer-weeks (and the taste draws) used in estimation. Out-of-sample statistics use a new sample of 6,000 consumer-weeks and new taste draws. Panel A: correlation coefficients are for number of firm-category shoppers  $D_{jk}$  and quantities  $Q_{jk}$ . Correlation statistics are for the 72 firm-category predictions. Panel B: mean absolute prediction errors are given by  $|s - s^*|$  where  $s$  is predicted and  $s^*$  is observed market shares as defined in text. B1 uses 72 firm-category market shares while B2 uses 8 category shares (the proportion of one-stop shoppers in category demand). Panel C: all columns sum to 1.

errors—one for each firm and category combination. We find that the average of these prediction errors is 0.008 for in-sample predictions (for both quantities and shoppers)—i.e., on average a firm's market share is predicted to be within about 1 percentage point of its observed value. A similarly small error is found for out-of-sample predictions. Figure 1 visualizes the predicted and observed market shares  $s_{jk}$  of each category for each firm in terms of number of shoppers (for the estimation sample).

The consumer's category demand is associated with a shopping choice  $c$  which may have either one or two stores. Substitution patterns between categories depend on this dimension of the model, as we saw in Section IIA. We therefore check the proportion of demand in each category from one-stop shopping choices, written  $s_k^{1ss}$ , in terms of quantities ( $\sum_f Q_{fk}^{1ss} / \sum_f Q_{fk}$ ) and shoppers ( $\sum_f D_{fk}^{1ss} / \sum_f D_{fk}$ ). There are eight such prediction errors: one for each category. Panel B2 of Table 4 shows that the average of these prediction errors is 0.004 in terms of quantities and 0.020 in terms of shoppers for in-sample predictions. A similar level of fit is found for the out-of-sample predictions.

Panel C of Table 4 moves from the category level to the firm level and considers the aggregate (across categories) market shares for the main firms in the market. This allows us to check that the model predicts the market share accurately for each firm both in-sample and out-of-sample.

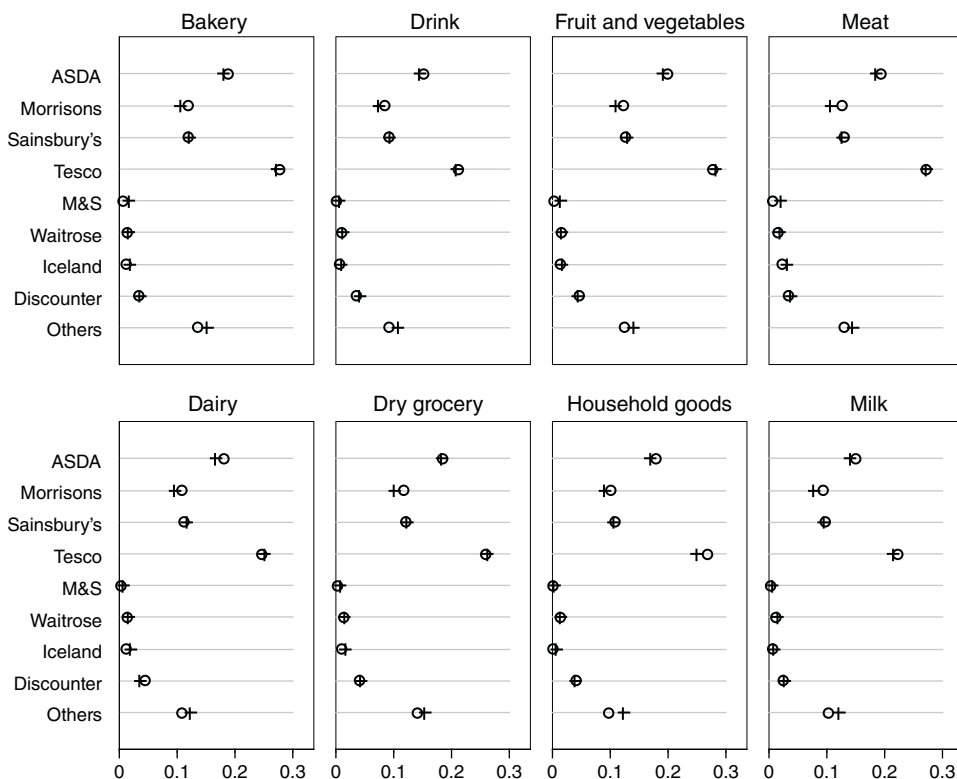


FIGURE 1. PREDICTED AND OBSERVED CATEGORY MARKET SHARES (*In Terms of Shoppers*)

*Note:* This figure shows observed (+) and predicted (o) market shares by category in terms of shoppers using the 6,000 consumer-weeks in the estimation sample (and their taste draws).

We now check how well the model predicts some other aspects of the shopping choices  $c$ . Table 5 looks at the in-sample fit for the market share 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 proportion of shoppers that shop only at one firm and the upper triangle gives the proportion that combine each pair of firms. Finally we provide a visual check of the spatial fit of the model. Figure 2 presents histograms of observed and predicted total shopping travel distances (to and from consumers' chosen stores) for the 6,000 consumer-weeks in the estimation sample. The histograms indicate that relatively few travel more than 30 km to and 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 percent of shoppers had a travel time of 20 minutes or less to their supermarket—a distance of about 15 km (30 km to and from) at standard driving speeds of 45 km/hour.

## V. Analysis of Supermarket Pricing

We now use the estimated model to analyze supermarket pricing. We first outline the pricing problem under two alternative organizational assumptions: supermarket

TABLE 5—OBSERVED AND PREDICTED MARKET SHARES BY FIRM PAIR

		ASDA	Morr	Sains	Tesco	M&S	Wait	Icel	Disc	Other
ASDA	Pred	0.144	0.011	0.011	0.024	0.002	0.001	0.004	0.008	0.025
	Obs	0.131	0.012	0.012	0.022	0.008	0.001	0.007	0.011	0.029
Morrisons	Pred		0.087	0.008	0.017	0.001	0.001	0.002	0.005	0.016
	Obs		0.073	0.004	0.012	0.001	0.001	0.002	0.009	0.018
Sainsbury's	Pred			0.098	0.023	0.001	0.002	0.001	0.004	0.014
	Obs			0.088	0.027	0.008	0.004	0.005	0.005	0.021
Tesco	Pred				0.209	0.002	0.005	0.006	0.010	0.045
	Obs				0.206	0.008	0.006	0.012	0.013	0.045
M&S	Pred					0.004	0.000	0.000	0.000	0.001
	Obs					0.004	0.002	0.001	0.001	0.004
Waitrose	Pred						0.011	0.000	0.000	0.003
	Obs						0.009	0.001	0.001	0.003
Iceland	Pred							0.013	0.001	0.004
	Obs							0.008	0.004	0.011
Discounter	Pred								0.029	0.008
	Obs								0.020	0.014
Other	Pred									0.149
	Obs									0.148

Notes: Predicted and observed market shares (in terms of shoppers) for each firm pair. The diagonal shows the proportion of consumers using the indicated firm only. Predictions and observations are for the 6,000 consumer-weeks (and taste draws) used in estimation.

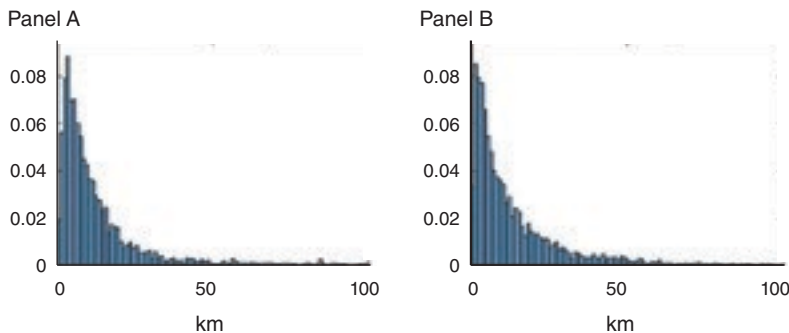


FIGURE 2. PREDICTED AND OBSERVED DISTANCES

Notes: The graphs display histograms of predicted (panel A) and observed (panel B) total shopping distances traveled (to and from stores) in kilometers for the 6,000 consumer-weeks (and taste draws) used in estimation. The height of each bar is the relative number of observations (number of observations in bin/total number of observations). The sum of the bar heights is 1.

pricing and independent category sellers. In VB we report the own- and cross-category demand elasticities implied by the estimated parameters. In VC we solve for the Nash equilibrium profit margins implied under the alternative organizational assumptions and compare them to external data on profit margins. We find that supermarket pricing fits the external data better. In the rest of the section we assume supermarket pricing and consider the two main policy-relevant questions of interest: we measure cross-category externalities and discuss their impact on market power, and we compare the impact of one-stop and two-stop shopper types on firms' pricing incentives.

Throughout this section we use the model's predictions of firm-category demands in a given week,

$$(47) \quad Q_{fk}(\mathbf{p}) = \sum_{i=1}^N \sum_{j \in \mathcal{J}_f} \sum_{c \in \mathcal{C}_{ij}} Q_{cjk}(\hat{\theta}, \mathbf{x}_{it}),$$

for the  $N$  consumers in the estimation sample, where  $Q_{cjk}(\hat{\theta}, \mathbf{x}_{it})$  is given by (19), and  $\mathcal{C}_{ij}$  is the set of shopping choice alternatives that include store  $j$ .<sup>39</sup> As we use only one period we suppress the  $t$  subscript in the rest of this section.

### A. Supermarket Pricing and Equilibrium Profit Margins

We compare two forms of organization: supermarkets, which set prices to maximize profit across all categories (internalizing cross-category effects), solving

$$\max_{p_{f1}, \dots, p_{fK}} \sum_{k=1}^K Q_{fk}(\mathbf{p})(p_{fk} - mc_{fk}),$$

and independent category sellers, which set prices to maximize category profit, solving

$$\max_{p_{fk}} Q_{fk}(\mathbf{p})(p_{fk} - mc_{fk}),$$

for  $k = 1, \dots, K$ . Here  $p_{fk}$  is the firm's (national) price and  $mc_{fk}$  the marginal cost. (The firms have a policy of national rather than storewise pricing: see footnote 13.)

We assume Nash equilibrium prices, which implies the following set of first-order conditions for each  $f$  and  $k$ :

$$(48) \quad \underbrace{\frac{Q_{fk}}{\partial Q_{fk}} + p_{fk}}_{\text{marginal category revenue } (mr_{fk})} + \chi_f \underbrace{\sum_{k' \neq k} \left( \frac{\partial Q_{fk'}}{\partial p_{fk}} \frac{\partial Q_{fk'}}{\partial Q_{fk}} (p_{fk'} - mc_{fk'}) \right)}_{\text{marginal externality } (me_{fk})} = mc_{fk},$$

where  $\chi_f$  is 1 for supermarket pricing and 0 for independent category sellers. This condition states that the marginal benefit of inducing an extra unit of demand for category  $k$  (by means of a price change)—i.e., the marginal revenue  $mr_{fk}$  plus the 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

$$(49) \quad \frac{\partial Q_{fk'}}{\partial p_{fk}} \bigg/ \frac{\partial Q_{fk}}{\partial p_{fk}},$$

<sup>39</sup> For all consumers  $i$  is week 78 (the midpoint of the 156-week sample period). We use the same taste draws as in estimation. If week 78 is not in the estimation sample for consumer  $i$  we draw a new time-specific taste  $\nu_{it}^\mu$ .

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  $p_{fk}$ . Letting  $\pi_{fk} = Q_{fk}(\mathbf{p})(p_{fk} - mc_{fk})$  and dividing (48) by price we obtain the following expression for the Lerner index:

$$(50) \quad \frac{p_{fk} - mc_{fk}}{p_{fk}} = \frac{1}{\left| \frac{\partial Q_{fk}}{\partial p_{fk}} \frac{p_{fk}}{Q_{fk}} \right|} - \frac{\chi_f}{p_{fk}} \sum_{k' \neq k} \left( \frac{\frac{\partial \pi_{fk'}}{\partial p_{fk}}}{\frac{\partial Q_{fk}}{\partial p_{fk}}} \right).$$

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 than this by the extent of the marginal externality (as a proportion of  $p_{fk}$ ).<sup>40</sup>

### B. Estimated Own- and Cross-Category Elasticities

The elasticities implied by the estimates are presented in Table 6 for six categories and three firms. The table consists of nine blocks of  $6 \times 6$  sub-matrices. The three  $6 \times 6$  within-firm elasticity matrices, along the principal block diagonal of the overall matrix, give own- and cross-elasticities for 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 (49) and the cross-category externality in (48) are positive. Some categories (e.g., meat) generate a much larger cross-elasticity than others (e.g., milk), which is likely to be a consequence of their relative size in the consumer's budget.

To decompose the cross-category complementarity effects into the consumer's discrete and continuous responses, Table 7 presents the  $3 \times 3$  submatrix of overall cross-category within-firm elasticities (for two firms, ASDA and Tesco) alongside the corresponding conditional elasticities that hold (discrete) store-category choices  $\mathbf{d}$  and shopping choices  $c$  constant and only allow continuous quantity choices to change. The cross-elasticities conditional on store choices are positive in sign. This shows that the cross-category complementarity derives from the consumer's shopping costs rather than from any intrinsic complementarity between the categories captured by  $\Lambda_{kk'}$ .

Returning to Table 6, note that 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 (8)): (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 Section IIA).

<sup>40</sup>In online Appendix H.1 we derive (50) from product-level first-order conditions. In online Appendix H.2 we show how group-specific prices (discussed in Section I) result in the same expression as in (50) where  $p_{fk}$  is a weighted average of the group-specific prices. For simplicity we ignore group specific prices in the notation in this section.



TABLE 6—CROSS ELASTICITIES AT FIRM-CATEGORY LEVEL FOR SELECTED CATEGORIES AND FIRMS

	ASDA						Tesco						Aldi					
	Bakery	Drink	Fruit	House	Meat	Milk	Bakery	Drink	Fruit	House	Meat	Milk	Bakery	Drink	Fruit	House	Meat	Milk
<i>ASDA</i>																		
Bake	-0.67	-0.22	-0.28	-0.28	-0.38	-0.05	0.09	0.08	0.12	0.13	0.17	0.02	0.00	0.00	0.01	0.00	0.01	0.00
Drink	-0.14	-1.30	-0.25	-0.25	-0.35	-0.05	0.06	0.11	0.10	0.12	0.14	0.02	0.00	0.01	0.01	0.00	0.01	0.00
Fruit	-0.14	-0.18	-0.65	-0.25	-0.37	-0.04	0.06	0.07	0.15	0.11	0.15	0.02	0.00	0.00	0.02	0.01	0.01	0.00
House	-0.14	-0.12	-0.26	-1.12	-0.36	-0.05	0.07	0.08	0.11	0.19	0.16	0.02	0.00	0.00	0.01	0.01	0.01	0.00
Meat	-0.12	-0.17	-0.25	-0.23	-0.84	-0.04	0.06	0.07	0.11	0.12	0.21	0.02	0.00	0.00	0.01	0.00	0.01	0.00
Milk	-0.13	-0.20	-0.23	-0.24	-0.36	-1.10	0.06	0.08	0.10	0.12	0.15	0.04	0.00	0.00	0.00	0.00	0.01	0.00
<i>Tesco</i>																		
Bake	0.05	0.06	0.07	0.07	0.10	0.01	-0.62	-0.17	-0.27	-0.29	-0.34	-0.05	0.00	0.00	0.01	0.00	0.00	0.00
Drink	0.03	0.07	0.06	0.06	0.08	0.01	-0.12	-1.31	-0.23	-0.24	-0.28	-0.05	0.00	0.01	0.01	0.00	0.01	0.00
Fruit	0.04	0.05	0.09	0.06	0.10	0.01	-0.14	-0.16	-0.70	-0.26	-0.34	-0.04	0.00	0.00	0.01	0.00	0.00	0.00
House	0.04	0.05	0.06	0.10	0.10	0.01	-0.14	-0.16	-0.24	-1.04	-0.32	-0.05	0.00	0.00	0.01	0.01	0.01	0.00
Meat	0.04	0.05	0.07	0.07	0.14	0.01	-0.13	-0.15	-0.25	-0.25	-0.83	-0.04	0.00	0.00	0.00	0.00	0.01	0.00
Milk	0.03	0.06	0.06	0.07	0.10	0.02	-0.13	-0.18	-0.24	-0.27	-0.32	-1.08	0.00	0.00	0.01	0.00	0.00	0.00
<i>Aldi</i>																		
Bake	0.09	0.05	0.12	0.07	0.14	0.02	0.15	0.08	0.17	0.19	0.18	0.02	-0.88	-0.24	-0.53	-0.32	-0.39	-0.07
Drink	0.04	0.12	0.09	0.08	0.14	0.01	0.06	0.19	0.16	0.14	0.15	0.02	-0.13	-1.95	-0.46	-0.35	-0.49	-0.06
Fruit	0.05	0.05	0.18	0.07	0.12	0.01	0.07	0.08	0.20	0.15	0.12	0.02	-0.14	-0.22	-1.04	-0.27	-0.34	-0.06
House	0.03	0.05	0.09	0.14	0.11	0.01	0.07	0.09	0.15	0.24	0.14	0.03	-0.14	-0.28	-0.45	-1.55	-0.39	-0.07
Meat	0.06	0.08	0.13	0.10	0.27	0.02	0.06	0.10	0.13	0.16	0.31	0.02	-0.13	-0.29	-0.43	-0.30	-1.46	-0.06
Milk	0.03	0.07	0.12	0.10	0.14	0.04	0.07	0.09	0.16	0.13	0.13	0.04	-0.16	-0.25	-0.50	-0.36	-0.44	-1.54

Note: Each cell is elasticity of row demand with respect to column price.

TABLE 7—WITHIN-FIRM CROSS-CATEGORY ELASTICITY DECOMPOSITION

	Conditional			Unconditional		
	Bakery	Fruit	Meat	Bakery	Fruit	Meat
<i>ASDA</i>						
Bakery	-0.373	0.005	0.020	-0.674	-0.282	-0.379
Fruit	0.003	-0.232	0.002	-0.136	-0.646	-0.370
Meat	0.007	0.001	-0.261	-0.124	-0.250	-0.836
<i>Tesco</i>						
Bakery	-0.367	0.006	0.019	-0.622	-0.268	-0.342
Fruit	0.003	-0.274	0.002	-0.137	-0.700	-0.337
Meat	0.007	0.001	-0.271	-0.130	-0.250	-0.832

Notes: All elasticities are within-firm. Each cell is elasticity of row demand with respect to column price. Conditional elasticities hold discrete choices ( $\mathbf{d}, c$ ) constant and allow only continuous choices to change. Unconditional elasticities allow the consumer to change shopping choice  $c$  and the store  $j \in c$  used for each category.

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 (50) 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 (50) for  $\chi_f = 1$ ), which results in the firm setting prices at a lower level than otherwise. Second, the own-price elasticities vary across firms in a plausible way: they are higher for the discounter (Aldi) than for the Big Four firms, which

may reflect (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  $6 \times 6$  blocks give interfirm 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 large market shares) is small (e.g., see the top-right  $6 \times 6$  block) compared to the opposite price elasticities. Note that the pattern of elasticities within these off-diagonal blocks suggests 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 (8))—e.g., in the top-middle block a change in the price of Tesco Meat has a higher proportional effect on ASDA Meat (0.21) than ASDA Drink (0.14) because of two-stop shoppers who switch stores for Meat only.

### *C. Predicted and Observed Profit Margins*

In this section we compare the margins (i.e., the Lerner index) implied by the model with bounds to profit margins calculated using external accounting data from competition inquiries (CC 2000, 2008). This allows us to check whether the assumption of supermarket pricing is validated by external data. We do this comparison at an overall level (across all categories) as well as for a specific category (milk) for which there is relatively accurate margin data.

The margins reported by the CC are based on firms' accounting data and cannot be unambiguously mapped to our theoretical margin concept for two reasons. (The issues here are common when dealing with accounting data on costs and revenues. For instance, Nevo 2001 discusses similar challenges when validating estimated margins with external data.) First, the CC only reports total revenues and total wholesale costs at the retailer level. Hence, we do not observe the marginal wholesale price and need to make an assumption about the vertical contract that led to the reported payments to manufacturers.<sup>41</sup> Second, it is ambiguous what fraction of labor costs should be considered marginal. We therefore provide bounds based on alternative assumptions about vertical contracts and the fraction of labor costs that are marginal. Further details on how we derive the bounds on margins are in online Appendix I.

To obtain the profit margins implied by the model we solve the system of first-order conditions (48) at estimated demand parameters under two alternative assumptions: supermarket pricing ( $\chi_f = 1$  in (48)) and independent category pricing ( $\chi_f = 0$ ). This gives a marginal cost  $mc_{fk}$  for each of the combinations of  $f$  and  $k$ . Based on these marginal costs a simple preliminary check on the two organizational assumptions is to ask whether either of them implies that marginal costs are negative. We find that all firm-category marginal costs are positive when we assume

<sup>41</sup> We do not explicitly model the interaction between manufacturers and retailers (as, for example, in Sudhir 2001 and Besanko, Dubé, and Gupta 2003). The external bounds that we calculate adopt an agnostic position as to whether there is double marginalization or efficient pricing. There is relatively little direct evidence that discriminates between these two alternative models of vertical contracting. Villas-Boas (2007) and Bonnet and Dubois (2010) use a structural model of demand to compare the implications of the two modeling assumptions and reject double marginalization in favor of efficient pricing (where the retailer optimizes against true vertical marginal costs).

supermarket organization but 14.8 percent of them are negative when we assume independent category sellers.

To assess the two organizational assumptions more formally, we present confidence intervals for the profit margins implied when  $\chi_f = 1$  and  $\chi_f = 0$ , respectively, and compare them with the external bounds to profit margins from the CC report. Panels B and C of Table 8 report 95 percent confidence intervals: the first column for the median margin in the milk category across firms, and the second column for the median margin across all categories and firms. Since each external margin is an industry-wide number, in panel C we weight the medians by firm-category revenue to reflect variation in firm and category sizes. The weighted median is higher because firms with larger market shares (such as the Big Four) tend to have greater market power. To calculate confidence intervals, we take 2,000 draws of the parameter vector from the (estimated asymptotic) distribution of our estimator where for each draw we compute margins using equation (50). The confidence intervals are then given by the 2.5th and 97.5th percentiles of the resulting distribution of medians.<sup>42</sup> If all the margins permitted by the external bounds fall outside the 95 percent confidence interval for one of the pricing assumptions, then this pricing assumption can be rejected at the 5 percent significance level (for all margins permitted by the external bounds).

Consider first the milk category. Here external bounds to margins are 0.20 and 0.34. Under the assumption of supermarket pricing the confidence intervals for margins—unweighted (0.22, 0.28), weighted (0.22, 0.33)—fall within the external bounds. Thus, we cannot reject (at the 5 percent level) the null hypothesis of supermarket pricing (for all margins within the permitted bounds). Under the assumption of independent category pricing, on the other hand, the confidence intervals—(0.65, 0.80) unweighted, (0.68, 1.01) weighted—fall outside the margins permitted by external bounds. Thus, we can reject (at the 5 percent level) the null hypothesis of independent category pricing.

Now consider all categories. Here the external bounds to margins are 0.16 and 0.52. Under the assumption of supermarket pricing the confidence intervals—(0.28, 0.31) unweighted, (0.37, 0.43) weighted—fall within the external bounds so we cannot reject the null hypothesis of supermarket pricing. Under the assumption of independent category sellers the confidence intervals—(0.71, 0.80) unweighted, (0.91, 1.09) weighted—fall outside the margins permitted by the external data and we can reject the hypothesis of independent category pricing (at the 5 percent level). Thus, even though the external data have quite wide bounds, we can reject the null hypothesis of independent category sellers. We cannot reject the null hypothesis of supermarket pricing.<sup>43</sup> In the rest of this section we use marginal costs under the assumption of supermarket pricing.

<sup>42</sup>The same 2,000 draws are used to generate the CIs in Tables 9 and 10. As a robustness check on the number of draws, we calculated the CIs in Table 8 using 5,000 draws and found the CIs were almost unchanged: for example, the confidence intervals for weighted margins were (0.23, 0.33) for milk and (0.37, 0.43) for all categories under supermarket pricing, and (0.71, 1.01) for milk and (0.92, 1.09) for all categories under independent category sellers.

<sup>43</sup>Alternatively, if supermarket pricing is taken as given, the confidence intervals for  $\chi_f = 1$  can be used to test the null hypothesis that the model is correct, which, based on the same arguments as above, cannot be rejected.

TABLE 8—PREDICTED PROFIT MARGINS AND OBSERVED BOUNDS TO MARGINS

	Milk	All categories
<i>Panel A. Bounds to margins from external data</i>		
A1 [lower bound]: Retail margin; labor included in marg. cost	0.20	0.16
A2 [upper bound]: Full vertical margin; labor excl. from marg. cost	0.34	0.52
<i>Panel B. Median predicted margins: 95 percent confidence intervals</i>		
B1. Supermarket pricing, $\chi_f = 1$ in equation (50)	(0.22, 0.28)	(0.28, 0.31)
B2. Independent category sellers, $\chi_f = 0$ in equation (50)	(0.65, 0.80)	(0.71, 0.80)
<i>Panel C. Weighted median predicted margins: 95 percent confidence intervals</i>		
C1. Supermarket pricing, $\chi_f = 1$ in equation (50)	(0.22, 0.33)	(0.37, 0.43)
C2. Independent category sellers, $\chi_f = 0$ in equation (50)	(0.68, 1.01)	(0.91, 1.09)

Notes: Panel A gives bounds to profit margins using external data in CC inquiries. See online Appendix I for details. Panel B reports predicted median profit margins; medians are across categories and firms (All Categories) and across firms (Milk). Weighted medians are weighted by firm-category revenues from the estimation sample to allow for heterogeneity in firm market shares.

TABLE 9—PROFIT MARGINS AND CROSS-CATEGORY EXTERNALITIES

	All categories			Mean							
	Median	Mean	95 percent CI	Bakery	Dairy	Drink	Dry	Fruit	House	Meat	Milk
<i>Panel A. Profit margins</i>											
All firms	0.30	0.31	(0.30, 0.33)	0.31	0.26	0.25	0.33	0.44	0.24	0.42	0.25
Big Four	0.37	0.38	(0.36, 0.41)	0.37	0.20	0.31	0.43	0.56	0.29	0.59	0.26
Discounter	0.28	0.29	(0.27, 0.31)	0.14	0.28	0.22	0.32	0.51	0.23	0.39	0.19
<i>Panel B. Inverse own-category elasticity (absolute value)</i>											
All firms	0.75	0.78	(0.73, 0.84)	1.02	0.75	0.57	0.81	0.93	0.67	0.79	0.75
Big Four	0.98	1.04	(0.97, 1.14)	1.46	0.75	0.72	1.15	1.34	0.86	1.11	0.89
Discounter	0.80	0.83	(0.76, 0.90)	1.10	1.00	0.61	0.78	0.97	0.72	0.84	0.58
<i>Panel C. Marginal externality <math>me_{fk}/p_{fk}</math></i>											
All firms	0.42	0.47	(0.43, 0.52)	0.71	0.49	0.32	0.48	0.49	0.43	0.36	0.49
Big Four	0.61	0.66	(0.60, 0.74)	1.09	0.55	0.41	0.72	0.78	0.57	0.52	0.63
Discounter	0.46	0.54	(0.48, 0.60)	0.96	0.72	0.39	0.46	0.46	0.49	0.45	0.39

Notes: Profit margins and externalities implied by the model in Nash equilibrium (with supermarket pricing). Figures in column All Categories average across categories, and figures in rows All Firms, Big Four, and Discounter average across firms of the stated type. By equation (50), figures in panel A equal those in B minus those in C. We focus on means (as opposed to medians) in this table in order to preserve this adding-up property.

#### D. Market Power and Cross-Category Externalities

With elasticities and marginal costs in hand we now analyze the extent to which cross-category externalities abate market power. Panel A of Table 9 reports profit margins for each category for alternative firm types. Recall from equation (50) that the profit margin may be decomposed as the category's inverse elasticity minus its marginal externality on other categories (as a fraction of  $p_{fk}$ ). We report these two components in Table 9: the inverse elasticity in panel B and the marginal cross-category externality in panel C. To preserve the adding-up property of equation (50), we report means rather than medians (medians are reported for All Categories for comparison). Panel A is thus the corresponding figure in panel B minus its counterpart in panel C.

The overall mean (across all categories and firms) is 0.31 as reported in the top cell of the second column. Profit margins are highest for the Big Four firms, which is not surprising given their large market shares. The inverse elasticities in panel B are the profit margins that we would have obtained if we had assumed that observed category prices are generated by independent category sellers rather than supermarkets (i.e., if we had set  $\chi_f = 0$  in (50) to back out marginal costs).<sup>44</sup> For the mean across all categories, profit margins under independent category pricing are more than double those with supermarket pricing (given in the first row of panel A). This shows that cross-category effects play an important role in correctly assessing market power in the supermarket industry.

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 analogous to the concept of *upward pricing pressure* (see Farrell and Shapiro 2010) 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; the marginal externality measures the downward pricing pressure implied.

As panel C of Table 9 reports, the marginal externality as a fraction of price, i.e.,  $me_{jk}/p_{jk}$ , is 0.47 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. Its magnitude indicates that this pro-competitive effect is economically significant. As a benchmark we note that it is greater than the magnitudes conventionally used to identify problematic merger cases (see CC 2011, ch. 4 for a discussion).

The table shows the variation in externalities by category. The externality for category  $k$  on any other category  $k'$  is given by the product of (i) the profit margin of category  $k'$  and (ii) the *diversion ratio* between  $k$  and  $k'$ . That is, the demand lost to the store on category  $k'$  per unit of demand lost on category  $k$ . A category has a large externality if these two factors are relatively high. Note that marginal externalities can be high even for categories (such as Bakery) that are a small share of consumer budgets (as shown in Table 2). This suggests that cross-category effects can be important even when measuring market power for a category that is a small fraction of the retailer's sales.

Now compare externalities by firm. The Big Four firms have larger externalities than average. This is in part a consequence of their higher profit margins (as reported in panel A) and in part a consequence of their shoppers having larger cross-category diversion ratios (as seen in the next subsection).

<sup>44</sup>The 95 percent confidence intervals presented in this table differ from those in Table 8 because they are confidence intervals of the means rather than medians. By comparing the confidence interval for "A: All Firms" with the second column of panel A of Table 8, we see that supermarket pricing is not rejected when using means, while the interval for "B: All Firms" shows that category pricing is rejected for all external margins when using means. That is, the conclusions in Section VC remain unchanged when using means instead of medians.

### E. Competitive Implications of Alternative Shopper Taste Types

We now partition consumers into two groups based on their tendency to visit one or two stores and compare their impact on market power. Each consumer in the model is characterized by a given  $(\mu, \alpha, \Gamma)$ -type which fully describes his tastes for the shopping choices in his choice set, up to the idiosyncratic term  $\epsilon$  (which is i.i.d. across shopping choices). A consumer's choice between one- and two-stop shopping depends on his  $(\mu, \alpha, \Gamma)$ -type: for instance, high shopping costs ( $\Gamma$ ) and/or a high utility  $(\mu - \alpha p)$  at the same store for all categories are conducive to one-stop shopping. After integrating out  $\epsilon$  we calculate the probability, for each  $(\mu, \alpha, \Gamma)$ -type, that the consumer makes a one-stop shopping choice.<sup>45</sup> If this probability is greater than or equal to 0.5 at the observed prices we place the  $(\mu, \alpha, \Gamma)$ -type in the one-stop group. Otherwise he is in the two-stop group. We refer to these two groups as one-stop shopper types and two-stop shopper types, respectively. Our goal is to assess which group abates market power to the greater extent. At the end of this subsection we consider an alternative partition based on  $\Gamma$  only.

To compare the impact of the two consumer groups on market power, we consider how they respond to a marginal price change for one firm-category combination at a time. These effects are shown in Table 10. Note that the grouping into one-stop and two-stop shopper types is based on consumers' behavior at observed prices and is therefore exogenous to these price changes.

We first calculate profit effects. Let  $\pi_f = \sum_k \pi_{fk}$  denote firm  $f$ 's profits (from all categories). Row A(i) of Table 10 shows that the partial derivative of firm  $f$ 's profit with respect to its price for category  $k$  is zero for each  $(f, k)$ -combination. This is true by construction since marginal cost has been calculated under the assumption that firms set each price to maximize profit. We now decompose the profit effect by shopper group  $g$ . Let  $g = 1$  for one-stop shopper types (defined above), and  $g = 2$  for two-stop shopper types. Let the profit derived from shopper group  $g$  be written  $\pi_f^g$ . Then the change in the firm's profits from the firm-category price increase can be decomposed:

$$\frac{\partial \pi_f}{\partial p_{fk}} = \frac{\partial \pi_f^1}{\partial p_{fk}} + \frac{\partial \pi_f^2}{\partial p_{fk}} = 0,$$

so that the effects for the two groups must be equal in magnitude and (if nonzero) opposite in sign. Rows A(ii)–A(iii) present the median group-specific profit effects along with 95 percent confidence intervals for these effects. The median effect is negative for one-stop shopper types and positive for two-stop shopper types. This pattern is seen for almost 90 percent of category store combinations. (The effects are larger for the Big Four because of their larger market shares.) The confidence intervals imply that one-sided tests at the 2.5 percent significance level reject the null hypotheses that median profit effects are positive for the one-stop types and that they are negative for the two-stop types, respectively. The same is true if tests are performed separately for Big Four and Discounters. Together the results indicate

<sup>45</sup>The probability is  $\sum_{c \in (c)=1} P_c(\mu, \alpha, \Gamma)$  where  $P_c(\mu, \alpha, \Gamma)$  is given by (18) and  $w_{it}(c, \mathbf{p}_t)$  depends on  $(\mu, \alpha)$  as discussed in Section IIB.



TABLE 10—PROFIT EFFECT OF A FIRM-CATEGORY PRICE INCREASE: ANALYSIS BY SHOPPER TYPES

Partition by:	$(\mu, \alpha, \Gamma)$						$(\Gamma)$
	All firms		Big Four		Discounters		All
	Median	CI	Median	CI	Median	CI	Median
<i>Panel A. Derivative of profit with respect to price</i>							
$\frac{\partial \pi_f^g}{\partial p_{fk}}$							
(i) $g = \text{all}$	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)	0.00
(ii) $g = 1$	−0.59	(−0.88, −0.47)	−3.69	(−5.40, −2.41)	−1.02	(−1.37, −0.71)	−0.19
[share < 0]	[0.89]	(0.82, 0.94)	[0.84]	(0.75, 1.00)	[1.00]	(0.92, 1.00)	[0.67]
(iii) $g = 2$	0.59	(0.47, 0.88)	3.69	(2.41, 5.40)	1.02	(0.71, 1.37)	0.19
[share > 0]	[0.89]	(0.82, 0.94)	[0.84]	(0.75, 1.00)	[1.00]	(0.92, 1.00)	[0.67]
<i>Panel B. Category own-price shopper elasticity</i>							
$\frac{\partial D_{fk}^g}{\partial p_{fk}} \frac{p_{fk}}{D_{fk}^g}$							
(i) $g = \text{all}$	−0.50	(−0.57, −0.45)	−0.42	(−0.45, −0.35)	−0.57	(−0.63, −0.51)	−0.50
(ii) $g = 1$	−0.39	(−0.45, −0.37)	−0.31	(−0.37, −0.29)	−0.51	(−0.56, −0.43)	−0.37
(iii) $g = 2$	−0.64	(−0.68, −0.56)	−0.51	(−0.54, −0.44)	−0.66	(−0.71, −0.59)	−0.59
<i>Panel C. Cross-category shopper diversion ratio</i>							
$\sum_{k' \neq k} \frac{\partial D_{fk'}^g}{\partial p_{fk}} / \frac{\partial D_{fk}^g}{\partial p_{fk}}$							
(i) $g = \text{all}$	3.76	(3.51, 3.89)	4.55	(4.39, 4.67)	4.02	(3.78, 4.20)	3.76
(ii) $g = 1$	5.11	(4.79, 5.21)	5.64	(5.39, 5.74)	5.29	(4.99, 5.43)	5.43
(iii) $g = 2$	2.31	(2.23, 2.44)	3.06	(2.99, 3.17)	2.53	(2.39, 2.72)	2.79

Notes: All figures are medians across firm-category combinations for firms within stated type. Figures in parentheses are 95 percent confidence intervals.

that one-stop shopper types constrain supermarket prices (and hence abate market power) more than two-stop shopper types.

The next two panels in the table explore the factors underlying this finding. The first-order condition (50) implies that the impact of a firm-category  $(f, k)$  price change on profit hinges on two main factors: (i) the own-price elasticity of category  $k$  demand and (ii) the marginal cross-category externality for firm  $f$ . Indicators for these two factors are presented for each consumer type in panels B and C of Table 10. We measure demand responses in these panels using the number of shoppers  $D_{fk}$  for each category (defined analogously to (47) using (20)) which gives a simple count measure of category demand that is easy to interpret and can be added across categories. We decompose  $D_{fk}$  by consumer group as  $D_{fk} = D_{fk}^1 + D_{fk}^2$ , where  $D_{fk}^g$  denotes the number of shoppers of group  $g$ .

Panel B of Table 10 considers own-price effects in terms of shoppers. Two-stop shopper types have higher own-price demand elasticities. This is consistent with the intuition that shoppers that tend to visit two stores can swap stores for a given category at relatively little cost.

Panel C turns to cross-category demand effects. To measure these we use the cross-category diversion ratio in terms of shoppers, i.e.,

$$(51) \quad \sum_{k' \neq k} \frac{\partial D_{fk'}^g}{\partial p_{fk}} / \frac{\partial D_{fk}^g}{\partial p_{fk}},$$

where the numerator and denominator of this ratio are both negative. In the case of the numerator this is because the categories for a given firm  $f$  are complements. The ratio (51) is the total number of shoppers lost by firm  $f$  for categories other than  $k$  for every shopper (in group  $g$ ) that stops buying category  $k$ . We find a strong difference between shopper types: the median diversion ratio for one-stop shopper types (5.11) is more than double that of two-stop shopper types (2.31).

Taken together the own- and cross-category effects of a price change, shown in panels B and C, explain why one-stop shopper types constrain the market power of the firms more than the average shopper: such shoppers (i) generate much larger than average cross-category demand effects per marginal consumer (panel C), and (ii) this effect is strong enough to outweigh the differences between one- and two-stop shopper types in terms of own-category demand elasticity (panel B).

In the last column we consider an alternative partition of consumer types by shopping costs ( $\Gamma$ ) only. Types with above-median shopping costs (for this classification defined as the cost of visiting a second store and traveling 10 km) are now classified in group  $g = 1$  and the remaining consumers in group  $g = 2$ . The results are similar despite this partition being less strongly associated with one-stop/two-stop shopping behavior than that based on the full set of tastes  $(\mu, \alpha, \Gamma)$ .

### F. Robustness

The results in Section V used Model 2 from Section IV. In this section we refer to this as the baseline model. We now consider four alternative specifications of the model. We discuss these specifications before showing that the main findings of the paper are robust.

The model labeled Ind  $p_{jk}$  changes the variable used for prices. It has price indices using weights that are computed using individual budget shares rather than budget shares for specific demographic groups (as done in the baseline model). The construction of these individual-specific price indices is described in online Appendix C.2.

The model labeled Alt  $dist_{ij}$  uses an alternative variable for distance. Instead of the sum of the distances from the consumer to each store and back we use the minimum distance the consumer would travel if he went in a triangle between home, store  $j$ , and store  $j'$ . This only makes a difference to the distance variable when the consumer is a two-stop shopper. Thus, distance when  $n(c) = 2$  is now given by  $dist_{ic} = (dist_{ij} + dist_{jj'} + dist_{ij'})$  instead of  $2(dist_{ij} + dist_{ij'})$ . This allows for the possibility that the consumer takes advantage of geographic synergies when visiting the two stores.

The model labeled Alt  $\Lambda_{kk'}$  estimates a different set of variable utility interaction parameters than in the baseline model. (These are bakery and dry, dairy and meat, and drink and milk). Cross-price variables in the  $\mathbf{Z}$  vectors, discussed in IIIA, are modified to reflect the changes in interactions.

Finally the model labeled Ind  $\Lambda_{kk'}$  allows for individual (observed and unobserved) consumer heterogeneity in the quadratic second-order terms (for  $k' \neq k$ ). As household size is one of the most important forms of heterogeneity we use the specification

$$\Lambda_{ikk'} = \Lambda_{kk'}(1 + \lambda_1 1[hz_i = 2] + \lambda_2 1[hz_i > 2] + \sigma_5 \nu_{ikk'}^\Lambda),$$

TABLE 11—ROBUSTNESS

All firms, all categories	Baseline	Ind $p_{jk}$	Alt $dist_{ij}$	Alt $\Lambda_{kk'}$	Ind $\Lambda_{kk'}$
<i>Panel A. Margins and externalities</i>					
Margin $(p_{jk} - mc_{jk})/p_{jk}$	0.30	0.32	0.30	0.30	0.29
Externality $me_{jk}/p_{jk}$	0.42	0.43	0.43	0.44	0.42
<i>Panel B. Derivative of profit with respect to price</i>					
1-stop shopper types	−0.59	−0.51	−0.66	−0.62	−0.58
[share < 0]	[0.89]	[0.89]	[0.89]	[0.88]	[0.83]
2-stop shopper types	0.59	0.51	0.66	0.62	0.58
[share > 0]	[0.89]	[0.89]	[0.89]	[0.88]	[0.83]

Notes: Entries are medians for all firms and all categories and therefore can be compared to the corresponding medians in Table 9 for panel A and Table 10 for panel B. The baseline model is the model used elsewhere in Section VI (Model 2 in Section V). Parameters for the other models are in online Appendix J.

where  $(\lambda_1, \lambda_2, \sigma_5)$  are additional parameters and the terms  $1[hz_i = 2]$  and  $1[hz_i > 2]$  are indicator variables for household size. The term  $\nu_{ikk'}^\Lambda$  is an i.i.d. random draw from a standard normal distribution. In addition to the variables in  $\mathbf{Z}_{iicjk}^Q$  and  $\mathbf{Z}_{iicjk}^D$  in the baseline specification we include, for each category, the following two variables: indicators for whether household size is 2, and for whether it is greater than 2, each interacted with the mean price of all categories other than  $k$  in the stores in the relevant shopping choice.

We check for robustness to these alternatives by comparing their implications for the main results discussed in Sections VD and VE of the paper. This is done in Table 11. Panel A of the table presents the median profit margins and externalities, across all firms and categories, which we use in Table 9 to assess the pro-competitive effects of supermarket organization. Panel B compares the marginal profit effects of one-stop and two-stop shopper types as we did in Table 10. The table shows these alternative specifications give results that are very similar to those we found for our baseline model. The parameters for the alternative specifications are given in online Appendix J.

## VI. 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 a multi-store multi-category model for estimation of consumer demand, relevant for the analysis of pricing in such settings. We estimate the model using data from the supermarket industry in the United Kingdom. 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 on market power of shopper types inclined to one-stop and two-stop shopping.

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 one-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 United Kingdom were tightened in the 1990s to protect town center retailing, while a law in France (*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 shopping types, we find that when supermarkets increase the price of a category marginally they lose profits earned on one-stop shopper types and gain profits from two-stop shopper types, which implies that the former constrain supermarket prices more than the latter. 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 one-stop (or core) shoppers, when the firms also sell to two-stop (or cross) shoppers. More generally, the finding indicates that the presence of consumers inclined toward two-stop shopping (e.g., those with low shopping costs) does not necessarily enhance competitive pricing incentives.

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