Working paper on store level demand estimation

Summary

1. This paper investigates empirically how consumers view different grocery retail offers as substitutes for one another. Using store level data, we employ standard econometric methods to estimate a model of U.K. demand for groceries. The estimation results yield measures of rivalry between stores of different sizes and of different fascias. These measures of rivalry are informative for our assessment of market definition.

2. Our preliminary results focus on rivalry between stores of different sizes and suggest that, in response to a hypothetical price increase by their preferred store, the consumers' first choice for substitution would be a store of similar size. Second choice would be a large store rather than a small store, implying that small stores are more constrained by larger stores than large stores are by smaller stores. Possible extensions of the model may include more explicitly accounting for consumer heterogeneity in geographic location and price sensitivity.

Model summary and results

3. In this paper, we apply standard econometric methods to estimate demand in differentiated product industries with product level data. We treat each store as a product that is differentiated along various observed and unobserved product characteristics. We assume that consumers base their decision where to shop for groceries on these characteristics. The model includes shopping alternatives that are not part of our sample of stores—we term these the "outside option". Differences in store market shares are indicative of how consumers value each shopping alternative, which is described in terms of a store price measure and a set of store

characteristics, such as the size of the store, the presence of a café, parking at store, pharmacy, opening hours etc.

4. We use store level data from the grocery retailers' responses to our main party questionnaire to estimate the parameters that affect consumer choice (see appendix 1 for a detailed presentation of the model). Our estimation sample contains 3,297 stores in the UK whose net sales area is at least 280 square metres. This sample includes stores of all main fascias, but due to data limitations largely excludes Booths, Iceland and regional Co-op stores as well as those of the Limited Assortment Discounters (i.e. Aldi, Lidl and Netto).[1] Stores for which we do not observe grocery revenue and net sales area, as well as stores with a net sales area below 280 sq m, belong to the "outside option".

5. Our store level price measure is based on a basket of generic grocery products. More details on how it is constructed and some summary statistics are provided in appendix 3. This price measure varies mostly across chains of stores, but also within most chains. Our estimate of consumer price sensitivity is therefore not only driven by price variation across chains. In appendix 1, we discuss in more detail how we alleviate estimation bias due to unobserved differences in retail offer across chains and stores.

6. Together with the observed market shares, the estimated parameters of the consumer choice model allow us to make some predictions on how consumers would react to a hypothetical change in the relative price of a specific store. Although hypothetical, these "out-of-sample" predictions can be used to calculate measures of rivalry between stores of different sizes and fascias. In particular, we compute

[1] When we observe grocery revenue and net sales area for one of these stores, we include these to predict diversion ratios, but these stores are not used in the estimation of the consumer choice model. See appendix 1 for more details.

diversion ratios for a hypothetical price change at a set of stores. A diversion ratio from stores of retail chain A to stores of retail chain B represents the share of revenue lost by chain A that is captured by B after A has increased its price. This measure of rivalry gives us an indication on how consumers rank different substitute alternatives. For example, when the diversion ratio from A to B is larger than from A to C, then it would appear that B imposes a stronger competitive constraint on A than C.

7. We partition stores into ten size groups so that each has a similar number of stores, and estimate for each size group a set of diversion ratios.[2] For example, we consider a scenario where all stores of chain A in a given size group increase their price by 1%. An estimated diversion ratio (in percentage terms) of 20 from chain A to chain B within the same size group suggests that out of each pound in revenue lost by the stores of chain A, 0.2 pounds are gained by stores of chain B.

8. In this paper, we focus on measures of rivalry between stores of different sizes: the following tables present diversion ratios for a number of size categories. More detailed estimation results can be found in Appendix 2. Table 1 presents the estimated diversion ratios for four pricing scenarios in size group 3 (stores with a net sales area ranging from 610 to 780 sq metres). The first scenario is the case of a 1% price increase by all Co-op Main stores that belong to group 3. We consider the sums of diversion ratios between stores of different size groups. For example, the figure in the first line of column (I) indicates that the 381 stores in group 1 would gain 0.205% of the revenue lost jointly by all Co-op Main stores in group 3. In contrast, the 382 stores in group 9 would gain 2.85% of the revenue lost by all Co-op stores in group 3.

[2] As laid out in more detail in the May 2007 market definition working paper, we consider that store size captures aspects of the overall retail offer of any given grocery outlet, some of which we do not observe.

9. Stores of similar size (ie stores in the same size group, in table 1 this is group 3) are estimated to gain most from a price increase by stores of a competing chain. In the scenario in column (I) of table 1, for example, 80.3% of the revenue lost by Co-op Main stores is estimated to go stores in the same size group, which leaves 19.7% of lost revenue diverted to stores in other groups and the outside option The estimated diversion to the outside option is reported in the last line of Table 1.

10. In all scenarios, the combined revenue gains of stores in other groups increase with size. These results suggest that stores in group 3 are constrained more by larger stores than by smaller stores. The estimated diversion ratios between groups are of similar magnitudes in all scenarios. As we discuss in more detail in the appendix, this finding is partly driven by the assumptions of our empirical model.

Table 1: Estimated diversion ratios for four pricing scenarios in group 3

	Size group	Number of stores	Scenario			
			1% price increase by all [✂] stores in group 3	1% price increase by all [✂] stores in group 3	1% price increase by all [✂] stores in group 3	1% price increase by all [✂] stores in group 3
1	280=<430	381	0.205	0.236	0.224	0.216
2	430=<610	376	0.299	0.345	0.327	0.315
3	610=<780	384	80.3	74.2	76.5	79.2
4	780=<990	366	0.481	0.555	0.525	0.506
5	990=<1290	379	0.737	0.849	0.805	0.776
6	1290=<1720	376	1.06	1.23	1.16	1.12
7	1720=<2320	382	1.54	1.77	1.68	1.62
8	2320=<3220	387	2.31	2.66	2.52	2.43
9	3220=<4170	382	2.85	3.29	3.11	3
10	4170=<	382	3.87	4.46	4.23	4.07
	Outside option		6.4	10.4	8.9	6.7

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

11. We have also considered scenarios of hypothetical price increases in the other nine size groups. The following tables present the estimated diversion ratios for groups 6 and 8; tables for the other groups can be found in appendix 2. Similar to the results presented in Table 1, competing stores of similar size stand to gain most from a hypothetical price increase. In addition, when it comes to stores of different sizes, larger stores tend to provide a greater competitive constraint than smaller stores, as indicated by the larger predicted share of revenue diverted to these stores.

Table 2: Estimated diversion ratios for four pricing scenarios in group 6

	Size group	No. of stores	Scenario				
			1% price increase by all [✄] stores in group 6	1% price increase by all [✄] stores in group 6	1% price increase by all [✄] stores in group 6	1% price increase by all [✄] stores in group 6	1% price increase by all [✄] stores in group 6
1	280=<430	381	0.238	0.241	0.242	0.299	0.256
2	430=<610	376	0.348	0.351	0.352	0.436	0.374
3	610=<780	384	0.51	0.515	0.517	0.639	0.549
4	780=<990	366	0.559	0.565	0.567	0.701	0.602
5	990=<1290	379	0.857	0.865	0.869	1.07	0.921
6	1290=<1720	376	77.8	77.6	77.3	72.2	76.1
7	1720=<2320	382	1.79	1.81	1.82	2.24	1.93
8	2320=<3220	387	2.69	2.71	2.72	3.37	2.89
9	3220=<4170	382	3.31	3.35	3.36	4.15	3.56
10	4170=<	382	4.5	4.54	4.56	5.64	4.84
	Outside option		7.4	7.5	7.7	9.3	8

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 3: Estimated diversion ratios for four pricing scenarios in group 8

	Size group	No. of stores	Scenario			
			1% price increase by all [✂] stores in group 8	1% price increase by all [✂] stores in group 8	1% price increase by all [✂] stores in group 8	1% price increase by all [✂] stores in group 8
1	280=<430	381	0.24	0.26	0.29	0.333
2	430=<610	376	0.35	0.379	0.423	0.486
3	610=<780	384	0.513	0.556	0.621	0.713
4	780=<990	366	0.563	0.61	0.681	0.782
5	990=<1290	379	0.862	0.934	1.04	1.2
6	1290=<1720	376	1.25	1.35	1.51	1.73
7	1720=<2320	382	1.8	1.95	2.18	2.5
8	2320=<3220	387	79.1	76.5	74.7	70.7
9	3220=<4170	382	3.34	3.61	4.03	4.63
10	4170=<	382	4.53	4.9	5.47	6.29
	Outside option		7.5	9	9	10.6

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Main findings

12. Our estimates imply that, in response to a hypothetical price increase, consumers are most likely to substitute towards a store of similar size. All else equal, stores of similar size are therefore closest competitors. Estimated diversion ratios between groups increase for groups of larger stores. Consumers are thus more likely to substitute towards a larger rather than a smaller store in response to a hypothetical price increase by any store. In other words, results suggest that stores of any size tend to be constrained more by larger competing stores than by smaller stores.

13. The estimated diversion ratios to the outside option should be interpreted keeping in mind that our estimation sample excludes some fascias that are likely to be part of the relevant market. Unfortunately, as long as these stores are technically part of the outside option, we are unable to identify consumer substitution patterns away from specific fascias or store sizes to these stores. Instead, they generally increase the diversion ratio to the outside option.

Appendix 1: Model and estimation

14. Following recent developments in the economic literature, we use a discrete consumer choice modelling approach to estimate store level demand for grocery retail offer. Several variants of this modelling approach have been used in the academic literature. For example, Smith ("Supermarket choice and supermarket competition in market equilibrium", Review of Economic Studies, vol. 71, pp. 235-263, 2004) employs this approach to estimate the UK demand for Groceries based on survey data. Nevo ("Mergers with differentiated products: the case of the ready-to-eat cereal industry", RAND Journal of Economics, vol. 31, pp. 395-421, 2000; "Measuring market power in the ready-to-eat cereal industry", Econometrica, vol. 69, pp. 307-342, 2001) estimates demand for ready-to-eat breakfast cereal in the US to assess market power and simulate horizontal mergers. The approach by Davis ("Spatial competition in retail markets: movie theaters", 2006), who uses retail level data to estimate a demand model for US movie theatres, is closest to our application.

15. Our aim is to formulate an empirical model of store level demand that relates observed store revenue to individual consumer shopping choices. In particular, we partition stores in size groups and specify the conditional indirect utility consumer i obtains from a typical shopping trip to store j in group g as a linear function of observed store characteristics (x_j, including price and location); unobserved store characteristics (v_j), which are characteristics that are not available to the data analyst but observable to market participants; a random utility component that is equal to all stores in group g for consumer i (ζ_{ig}); and a consumer-specific utility component (ε_{ijg}) that captures consumer i's deviation in utility from mean consumer utility of a typical shopping trip to store j:

(1) $U_{ijg} = x_j \beta + v_j + \zeta_{ig} + (1\text{-}\sigma_g)\, \varepsilon_{ijg}$,

where the main parameters to be estimated are β, which captures the marginal utility contributions of observed store characteristics (including price), and σ_g, the correlation of consumer preferences across stores belonging to the same group.

16. Because we focus on explaining store revenue rather than individual consumer shopping trips, we do not distinguish between consumer choice of store and in-store consumer choice of shopping basket (expenditure). These two decisions are likely to be dependent, in the sense that certain stores are more attractive for large basket shopping and others more for small basket shopping. We account for this fact insofar as the inclusion of a consumer-group specific random utility component accounts for differences in consumer spending across stores. In this interpretation, consumer *i*'s difference in utility between stores in different groups (ζ_{ig}) would originate from her difference in spending in stores of group *g* from the average consumer, and the estimated σ_g would indicate how strongly consumer spending is correlated across stores of group *g*.

17. As consumers tend to allocate large basket shopping trips to larger stores, we partition stores into ten arbitrary size groups, with cut-off points chosen to roughly equalise the number of sampled stores in each size group.[3] As laid out in more detail in the May 2007 market definition working paper, we consider that store size captures aspects of the overall retail offer of any given grocery outlet. In this paper we also include a number of store characteristics such as price and opening hours. Yet, we do not observe some additional characteristics such as product range, which we aim to capture by our store size grouping. The significance of our estimation results will indicate whether this particular grouping of stores makes sense empirically. In particular, an estimate for σ_g close to zero would suggest that

consumer preferences for stores in a size group are not correlated, i.e. that stores in each of our defined groups actually do not share an unobserved characteristic.

18. Consumers may also buy groceries in non-grocery stores (such as Boots or Woolworths), as well as in grocery stores that due to data limitations are not part of our sample (stores with a net sales area of less than 280 sq m, limited assortment discounters, food specialists, and stores of the main fascia with missing data). We combine these alternatives into one "outside shopping option" grouped into a separate group (g=0) and normalize the mean indirect utility of a typical shopping trip to the outside option to zero. Consumers are assumed to choose between the stores in the market and their outside option based on common knowledge of all store characteristics and utility maximisation.

19. Under the "nested logit" assumption that both ζ_{ig} and $(1-\sigma_g)\varepsilon_{ij}$ are i.i.d. extreme-value distributed with mean zero, the expected probability of a potential consumer to shop at store j in group g depends only on store characteristics and on unobserved group characteristics. This probability can be shown to translate directly into an estimable relationship between the logarithm of store j's market share (s_j) relative to the share of the outside option (s_0), its characteristics (x_j and v_j), and the logarithm of its share of group revenues ($s_{j|g}$):[4]

$$(2) \qquad \log(s_j)-\log(s_0) = \sigma_g \log(s_{j|g}) + x_j \beta + v_j \,,$$

[3] Store grouping is based on net sales area. A comparison of results for two different sets of cut-off points suggests a grouping based on the following cut-off points (see below for more details): 430, 610, 780, 990, 1290, 1720, 2320, 3220 and 4170 square meters.

[4] Our exposition follows Berry ("Estimating Discrete-Choice Models of Product Differentiation", RAND Journal of Economics, vol. 25, pp. 242-262, 1994) and Verboven ("International Price Discrimination in the European Car Market, RAND Journal of Economics, vol. 27, pp. 240-268, 1996), except that we include price in x_j. Verboven ("The nested logit model and representative consumer theory", Economics Letters, vol. 50, pp. 57-63, 1996) shows how this model of discrete and heterogeneous consumer choices can be interpreted as a model of a single representative consumer.

where σ_g and β contain the parameters to be estimated, with unobserved store characteristics v_j being the estimation error. In many empirical studies the "nesting parameter" σ_g is assumed to be the same across groups, but this need not be the case. We relax this restriction allowing σ_g to differ across 5 group pairs.

20. ***Geographic location.*** An important driver of a store's attractiveness is its geographic location. Although we rely on aggregate store level data, to the extent possible we include measures of location in x_j. For example, the probability that a particular consumer chooses a particular store is likely to decrease with the distance between his home or workplace and the store. We follow Davis (2006) in measuring consumer heterogeneity in distance to a store by including the counts of population and net daytime population inflow within 20 minutes drive-time as store characteristics. This allows us to control for differences in demographics around each store in our sample, but we are not explicitly estimating the consumer disutility of distance. A possible extension of the model would use detailed census data to estimate consumer disutility of distance directly.[5]

21. ***Data.*** To estimate equation 2 above, we calculate market shares based on revenue data from responses to the Main Party Questionnaire and a measure for the size of the market (including the outside option). For most stores, we have a series of revenue observations over time. However, data for a number of store characteristics including price are available only for one of the first six months of 2006. Our sample is therefore restricted to a cross-section of stores with market shares calculated from average weekly revenue in this time period.

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[5] This approach would follow Davis (2006) and Berry, Levinsohn and Pakes ("Automobile Prices in Market Equilibrium", Econometrica, vol. 63, 841-890, 1995).

22. For some stores revenue is reported per calendar month, while for other stores it is reported on a 4-weekly basis. Stores also differ in the length of the reported period, with some series of observations ending in May 2006 and other series ending in August 2006. For each store, we use up to seven revenue periods starting in 2006 and ending no later than August 2006, and calculate a store's average weekly revenue on the basis of the total number of days covered for this store. We exclude stores that have missing revenue data for January and February 2006, and stores whose weekly average revenue measure would be based on less than five non-missing revenue observations. We also exclude stores that close down before the end of August 2006 or that have gaps in their time series of revenue (possibly refurbishment-related).

23. We use store revenue from grocery products to calculate each store's market share. Most parties provided store revenue inclusive of VAT, customer returns and consumer savings (from promotions and price reductions), except [✂] and [✂]. [✂] reported store revenue net of VAT. We therefore adjusted the revenue of [✂] stores using a month-specific factor based on [✂] response to a follow-up question.[6] [✂] reported store revenue before deduction of customer savings from promotions. We are currently following up on [✂] in order to correct for this difference in reporting.

24. Stores for which we do not observe grocery revenue and net sales area, as well as stores with a net sales area below 280 sq m, are part of the outside option in our model. For a number of stores, we observe grocery revenue and net sales area but we lack data on other store characteristics (particularly the store price measure). Although we are not able to include this latter group of stores when we estimate the

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[6] [✂] provided the company-wide amount of VAT collected per month, as a percentage of net revenue, which allows us to mark up store grocery revenue by the average percentage of VAT collected on grocery products (assuming that non-grocery revenue is generally taxed with the full rate of 17.5%). For example, if the company-wide amount of VAT collected per month is 10% of net revenue in a given month, then our approximation for store grocery revenue including VAT is:
1.1*(total store revenue excluding VAT) - 1.175*(store non-grocery revenue excluding VAT).

consumer choice model, we include these stores in the computation of diversion ratios.

25. ***Market size.*** Our starting point is an "economic market" that combines all grocery stores in England, Scotland and Wales.[7] The share of each store depends on the size of the market. We may consider more narrow markets as starting points, however, the corresponding estimates may be biased by the fact that stores located close to the market boundaries – however defined – will also attract consumers from neighbouring markets.

26. Our measure of market size is based on data on average weekly consumer spending on groceries provided by CACI for the year 2006.[8] According to these estimates, consumer spending in England, Scotland and Wales in the categories food, non-alcoholic beverages, alcoholic beverages and personal care added up to about 1901 mn GBP for an average week in the first six months of 2006. We use this figure as the size of the U.K. economic market for groceries. In the first six months of 2006, the stores in our sample had combined average weekly revenues on grocery products of about 1300 mn GBP (including VAT). A value of 1901 mn GBP for the economic market would thus imply a market share of the outside option of about 32%, which seems to be a relatively high figure. But our outside option not only includes non-grocery stores that may sell grocery items, it also contains grocery stores that are not part of our sample because of data limitation, such as stores with a net sales area of less than 280 sq m, limited assortment discounters and food specialists.

[7] The term economic market here does not refer to the definition of the relevant market for the purpose of this inquiry. The delineation of the relevant market relates to the exercise of market power, whereas with the term economic market we refer to a monetary measure for aggregate U.K. demand for groceries.
[8] As the CACI data on weekly average spending relate to the full year of 2006, due to the importance of Christmas sales they are likely to slightly overestimate the weekly average for the first six months.

27. ***Store prices, price elasticities and diversion ratios.*** We include a store level price measure in x_j, which is based on a basket of generic grocery products such as "bread" and "tomatoes". Appendix 3 below provides more details on how the price measure is constructed and some summary statistics. It is likely that the quality of these products differs across stores of different chains, which in turn is likely to be reflected in prices. We include a chain-specific constant term to account for differences in average consumer evaluation of the chain's level of product quality, as well as other unobserved characteristics shared by all stores of a chain. The store price measure allows us to estimate the price sensitivity (the disutility of income) of consumers, which is a key element in calculating own- and cross-price elasticities between stores.

28. The nested logit model predicts that a store's own- and cross-price elasticities depend on the estimated coefficients on price (b_p, expected to be negative) and group share (σ_g), as well as the store's observed price (p_j) and group and market share ($s_{j|g}$, s_j). The formulae are provided below:

(3a) $\eta_{jjg} = b_p\, p_j\, (\,(1\text{-}\sigma_g)^{-1} - s_j - \sigma_g\,(1\text{-}\sigma_g)^{-1}\, s_{j|g}\,)$,

(3b) $\eta_{jkg} = \text{-}b_p\, p_j\, (\, s_j + \sigma_g\,(1\text{-}\sigma_g)^{-1}\, s_{j|g}\,)$,

(3c) $\eta_{jk'} = \text{-}b_p\, p_j\, s_j$,

where η_{jj} denotes the own-price elasticity of store j's revenue, η_{jkg} denotes the cross-price elasticity of the revenue with other stores in store j's group, and $\eta_{jk'}$ denotes the cross-price elasticity with stores in other size groups. In other words, the model predicts that, when store j increases its price by 1%, all else equal its revenue would decrease by η_{jj} %, the revenue of store k in the same size group would increase by η_{jkg} %, and the revenue of store k' in another group would increase by $\eta_{jk'}$ %.

29. The predicted diversion ratios between stores j, k and k' thus follow directly from the price elasticities and each store's U.K. revenue share. For example, the lost revenue share of store j equals $\eta_{jj}\, s_j$, while store k in group g gains revenue share given by $\eta_{jkg}\, s_k$, and the ratio of ($\eta_{jkg}\, s_k$) over ($\eta_{jj}\, s_j$) represents the share of j's lost revenue that is recovered by store k. Yet, rather than looking at diversion ratios between individual stores we consider diversion ratios between sets of stores. In particular, we consider the case that all stores of chain C in group g increase their price by 1%. In calculating the revenue lost jointly by these stores, we also have to include cross-effects between them. The revenue share lost by each store j of chain C now equals ($\eta_{jj} + \sum_{j'} \eta_{j'kg}$) s_j , where j' denotes another store of chain C in group g that is assumed to increase its price by 1%. The sum of these changes (decreases) in revenue share over all of C's stores in group g is the diverted revenue of chain C in group g (DS_{Cg}). The predicted gains in revenue share of each store k of other chains in group g and of each store k' in other groups again equal ($\eta_{jkg}\, s_k$) and ($\eta_{jk'}\, s_{k'}$). However, we calculate diversion ratios on the size group level, where the diversion ratio of chain C's stores in group g to other chains' stores in group g is the sum of ($\eta_{jkg}\, s_k$) over all other chains' stores, divided by the absolute value of DS_{Cg}. Similarly, we consider the diversion ratio of chain C's stores in group g to all stores in another group g' as the sum of ($\eta_{jk'}\, s_k$) over all stores in group g', divided by DS_{Cg}.

30. The price elasticity formulae (equations 3) illustrate that the error specification of an empirical model of demand can have restrictive implications for the predicted price elasticities. For example, the simple logit model, with σ_g=0 for all g, predicts that a price increase at store j leads consumers to substitute in equal proportions towards all other stores in the market; and the magnitudes of the elasticities depend on the estimated coefficient for price and store j's revenue share. In the nested logit model, instead, a store's own-price elasticity depends on the estimates of the price and

nesting parameters and its share in group and market revenues. The nested logit relaxes the substitution patterns imposed by the simple logit model, but it does remain somewhat restrictive. In particular, it still restricts consumer substitution to be proportional towards alternatives that belong to the same group.

31. ***Endogeneity.*** A general issue in demand estimation relates to the possible endogeneity of price or other store characteristics variables. In our model, the price variable is considered endogenous if it is related to unobserved store characteristics. For example, this will be the case if store *j*'s prices are dependent on its quality of services or other unobserved characteristics. If stores with higher service quality tend to charge higher prices but we do not observe service quality, simple regression estimates of the above equation will understate the price sensitivity of consumers. This reasoning also applies when prices are fixed across stores of a chain that operates a national pricing policy. Although prices may not vary across stores of the same fascia, unobserved service quality may vary. In case of national pricing, the relationship between prices and unobserved quality remains. Stores whose chain-dependent prices are low, relative to local cost or demand conditions, may have lower levels of unobserved service quality. In this case simple regression estimates of the above equation will also understate the price sensitivity of consumers. Based on a similar reasoning, store j's share of group revenue (sj|g) is likely to be correlated with unobserved store characteristics and therefore endogenous.

32. ***Instruments.*** An appropriate method to alleviate endogeneity bias in the parameter estimates is to use instrumental variable estimators, which require additional variables that are associated with the (potentially) endogenous explanatory variable but not associated with the estimation error. Berry, Levinsohn and Pakes (1995) argue that the number of competing products and the sums of their observed

characteristics are appropriate instruments for a product's price. We thus construct similar instruments based on all stores within a drive-time of 20 minutes around store *j*. We distinguish between competing stores that are operated by the same chain and stores operated by other chains. To instrument for store *j*'s share in group revenue, we also include the number of competitor stores in the same group within a drive-time of 20 minutes around store *j* and the sums of their characteristics, again distinguishing between stores of *j*'s own chain and other chains.

33. ***Other store characteristics.*** In addition to price, we include the following store characteristics in the model: net sales area, net sales area squared, the average number of staff at the store,[9] the average number of hours the store is opened per week[10] and indicator variables equal to one if the store has parking at store, a petrol forecourt, a pharmacy, one or more ATMs, a restaurant, and toilets. Table 4 below presents some summary statistics on these characteristics for the stores in our estimation sample. A standard assumption is that all store characteristics except price are exogenous. This assumption is unlikely to be critical in case of all physical store characteristics that have been determined prior to the sample period (net sales area, parking, petrol forecourt, etc.). To account for differences in unobserved service and product quality at the chain level, we include chain indicator variables (for Asda, Co-op Main, Marks & Spencer, Morrisons, Sainsbury's, Somerfield, Tesco, and Waitrose).

[9] For Marks & Spencer department stores, the number of staff of included all staff, most of which is not associated with the selling of groceries; for these stores, we therefore calculated a store estimate of staff based on a bivariate regression analysis of staff and average weekly revenue for stand-alone Marks & Spencer Simply Food grocery stores.
[10] In a number of cases, a store's opening hours are not observed for every week in the first half of 2006. The corresponding average is then calculated based on the week(s) for which opening hours are observed.

Table 4: Summary statistics for stores in estimation sample

Variable	Average	Minimum	Median	Maximum
Average weekly grocery revenue	377273.6	11180.53	253234.7	2.01E+06
Price measure (37-item basket)	2.8	2.33	2.68	4.49
Net sales area	2049.4	280	1494	9597
Number of staff (monthly avg.)	189.6	10.17	162.33	929.8
Opening hours (weekly avg.)	90.2	43	84	162.4
Parking at store	0.78	0	1	1
Petrol Forecourt	0.31	0	0	1
Pharmacy	0.18	0	0	1
ATMs	0.70	0	1	1
Restaurant/Café	0.37	0	0	1
Toilets	0.57	0	1	1
Population*	320.66	1.64	248.85	1461.47
Net daytime population inflow*	-163.81	-799.94	-123.79	664.8

Source: CC Analysis of MPQ responses (store revenue and characteristics) and CACI (demographics by census output area, 2006). Summary statistics cover 3279 stores that are part of the estimation sample. *Population figures are in thousands and for a drive-time of 20 minutes around each store.

34. We control for variation in demographics by including counts of population and the net daytime population inflow within 20 minutes drive-time around each store. Net daytime population inflow is the difference between population and daytime population as defined by the ONS.[11] These demographic variables are treated like exogenous store characteristics. The exogeneity assumption is appropriate, for example, if choice of location is constrained by the availability of land or if location is chosen endogenously but prior to the unobserved store characteristics that affect v_j.

[11] ONS "population" figures include all people that live but not necessarily work in an area, whereas "daytime population" figures include all people that are present during the day in an area (working or not working). The difference between daytime population and population thus measures net daytime population inflow; for example, this is negative for an area in which many people live but few people work.

Appendix 2: Estimates

35. Table 4 below presents the estimated coefficients for two econometric specifications of the model that base on different size group definitions: in specification 1, the size groups are defined such as to roughly equalize across groups the number of stores that are part of the estimation sample. In specification 2, the size groups are defined such as to roughly equalize across groups the number of stores that are in the prediction sample. The size cut-offs in specification 2 are somewhat narrower at the lower end of the size spectrum, which indicates that there is a relatively larger number of smaller stores in the prediction sample than in the estimation sample. Interestingly, the size cut-offs of specification 1 include the 1,400 sq m cut-off, whereas specification 2 does not. A useful feature of the nested logit model is that the size and significance of the estimated nesting parameters indicate whether the assumed grouping of stores is supported by the data. Therefore, a comparison of specifications 1 and 2 will also be informative regarding the economic validity of the 1,400 sq m cut-off.

Table 5: Nested logit coefficient estimates

	Specification 1: 10 size groups with cutoffs at 450, 670, 880, 1100, 1400, 1900, 2500, 3400 and 4300 sq m	Specification 2: 10 size groups with cutoffs at 430, 610, 780, 990, 1290, 1720, 2320, 3220 and 4170 sq m
Nesting parameters:		
$\sigma_{1,2}$	0.609***	0.855***
	(0.0216)	(0.0205)
$\sigma_{3,4}$	0.588***	0.815***
	(0.0219)	(0.0202)
$\sigma_{5,6}$	0.564***	0.784***
	(0.0219)	(0.0198)
$\sigma_{7,8}$	0.582***	0.782***
	(0.0223)	(0.0195)
$\sigma_{9,10}$	0.607***	0.808***
	(0.0235)	(0.0203)
Coefficients on store characteristics:		
Price measure	-1.589***	-0.893***
(endogenous)	(0.161)	(0.111)
Net sales area	0.000637***	0.000792***
	(0.0000322)	(0.0000253)
Net sales area squared	-5.71e-08***	-6.75e-08***

	(2.89e-09)	(2.31e-09)
Number of staff	0.00154***	0.000684***
(monthly average)	(0.000107)	(0.0000897)
Opening hours	0.00176***	0.000703***
(weekly average)	(0.000209)	(0.000177)
Parking at store	0.0450***	0.0463***
	(0.00947)	(0.00648)
Petrol Forecourt	-0.0178**	-0.00696
	(0.00703)	(0.00600)
Pharmacy	-0.00194	-0.000328
	(0.00576)	(0.00498)
ATMs	0.0103	0.00552
	(0.00748)	(0.00537)
Restaurant/Café	-0.00191	-0.0167***
	(0.00720)	(0.00597)
Toilets	0.0886***	0.0675***
	(0.00861)	(0.00648)
Population within 20 minutes	0.0000859***	0.0000395***
(in '000s)	(0.0000139)	(0.0000101)
Net daytime population inflow	0.000161***	0.0000826***
within 20 minutes (in '000s)	(0.0000212)	(0.0000155)
Chain-specific constant terms:		
Somerfield	[✂]	[✂]
Coop Main	[✂]	[✂]
Tesco	[✂]	[✂]
Marks and Spencer	[✂]	[✂]
Asda	[✂]	[✂]
Morrisons	[✂]	[✂]
Sainsbury's	[✂]	[✂]
Waitrose	[✂]	[✂]
Stores in estimation	3279	3279
R-squared	0.982	0.990
Root MSE	0.141	0.106
Range of F-Statistics on instruments in first stage	12.63 – 194.0	18.20 – 182.9

Source: CC Analysis of MPQ responses. Nested logit 2-step GMM estimation results with standard errors (robust to heteroskedasticity) in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Instruments for price and share in group revenues: Number and characteristics of stores of the same chain, of stores of other chains, of stores of the same chain in the same group, and of stores of other chains in the same group (all within a drive-time of 20 minutes).

36. All estimated nesting parameters are highly significant statistically, however, those for specification 2 exceed those of specification 1 in value. In addition, specification 2 has better estimation properties as measured by the R-squared and the root mean

squared error statistics. We conclude that the data generally support the notion that stores of similar size share an unobserved characteristic, and that the store grouping of specification 2 – which does not include 1,400 sq m as a cut-off point – seems to represent these similarities more accurately. We therefore use estimates based on this size grouping for our calculations of price elasticities and diversion ratios (based on the formulae in equations 3).

37. First-stage F-statistics suggest that our instrumental variables, which correspond to the variables typically used in this kind of demand estimation, are reasonably correlated with our endogenous variables.[12] All chain-specific constant terms are highly significant, except for the coefficients for [✂] and [✂] in specification 1. Most estimated coefficients for store characteristics are statistically significant and have the expected (positive) sign. The estimated coefficient on price is significantly negative in both specifications. Table 6 below summarises the price elasticities corresponding to the estimates from specification 2 by size group and chain.

Table 6: Summary of estimated own- and cross-price elasticities

Size group	Size range	Chain	No. of stores in estimation	Own price elasticity	Cross-price elasticity within group*	Cross-price elasticity outside group**
1		[✂]	[✂]			
	280=<430			-18.7	0.0326	5.61E-05
	280=<430			-18.6	0.0593	0.000102
	280=<430			-21	0.0664	0.000114
	280=<430			-21.8	0.0488	8.39E-05
	280=<430			-14.8	0.0645	0.000111
2	430=<610			-18.3	0.0297	7.44E-05
	430=<610			-18.6	0.0526	0.000132
	430=<610			-18.7	0.0908	0.000228
	430=<610			-21.6	0.0372	9.32E-05
	430=<610			-14.8	0.0699	0.000175
	430=<610			-20.4	0.0943	0.000236
3	610=<780			-11.3	0.0423	0.000207
	610=<780			-14.4	0.0213	0.000104
	610=<780			-14.6	0.043	0.000211
	610=<780			-12.9	0.0464	0.000227

[12] There are six first-stage regressions: one for price and one for each nesting parameter.

		[✂]	[✂]			
	610=<780			-16.9	0.0241	0.000118
	610=<780			-11.7	0.0434	0.000212
	610=<780			-16	0.0724	0.000354
4	780=<990			-14.4	0.0223	0.00012
	780=<990			-14.6	0.0432	0.000232
	780=<990			-12.9	0.0488	0.000262
	780=<990			-16.9	0.0291	0.000156
	780=<990			-11.7	0.0458	0.000246
	780=<990			-16	0.0911	0.000489
5	990=<1290			-12.3	0.013	0.00013
	990=<1290			-12.5	0.0275	0.000274
	990=<1290			-9.87	0.0215	0.000215
	990=<1290			-11.1	0.0301	0.0003
	990=<1290			-14.4	0.0181	0.00018
	990=<1290			-9.96	0.0292	0.000291
	990=<1290			-13.7	0.0429	0.000427
6	1290=<1720			-9.63	0.0195	0.00028
	1290=<1720			-12.3	0.0107	0.000153
	1290=<1720			-12.5	0.0216	0.000309
	1290=<1720			-9.87	0.0194	0.000277
	1290=<1720			-11.1	0.0214	0.000306
	1290=<1720			-14.4	0.0163	0.000233
	1290=<1720			-9.96	0.0297	0.000426
	1290=<1720			-13.7	0.0388	0.000556
7	1720=<2320			-9.53	0.0213	0.000445
	1720=<2320			-12.1	0.00942	0.000197
	1720=<2320			-9.76	0.0164	0.000342
	1720=<2320			-10.9	0.0233	0.000487
	1720=<2320			-14.3	0.00984	0.000206
	1720=<2320			-9.85	0.0296	0.000619
	1720=<2320			-13.5	0.0316	0.00066
8	2320=<3220			-9.53	0.0192	0.000595
	2320=<3220			-12.1	0.00841	0.000261
	2320=<3220			-9.76	0.0146	0.000454
	2320=<3220			-10.9	0.0212	0.000659
	2320=<3220			-14.9	0.00445	0.000138
	2320=<3220			-9.86	0.0273	0.000846
	2320=<3220			-13.6	0.0233	0.000723
9	3220=<4170			-10.9	0.0249	0.000808
	3220=<4170			-13.8	0.00512	0.000166
	3220=<4170			-11.1	0.0184	0.000596
	3220=<4170			-12.5	0.0274	0.000889
	3220=<4170			-11.2	0.0316	0.00103
10	4170=<			-10.9	0.023	0.000999
	4170=<			-11.1	0.0138	0.000602
	4170=<			-12.5	0.0236	0.00103
	4170=<			-11.2	0.0282	0.00123
	4170=<			-15.4	0.0244	0.00106

Source: Source: CC Analysis of MPQ responses. Based on nested logit estimation results. *Median estimated percentage change in market share of a store in the group, when the price of a store of row firm in the same group increases by 1%. **Median estimated percentage change in market share of a store in another group, when the price of a store of row firm in this group increases by 1%

38. The following tables present the estimated diversion ratios for a number of price scenarios in size groups 1, 2, 4, 5, 7, 9, and 10.

Table 7: Estimated diversion ratios for four pricing scenarios in group 1

	Size group	Number of stores	Scenario			
			1% price increase by all [✂] stores in group 1	1% price increase by all [✂] stores in group 1	1% price increase by all [✂] stores in group 1	1% price increase by all [✂] stores in group 1
1	280=<430	381	81.6	83.4	78.9	84.5
2	430=<610	376	0.273	0.249	0.287	0.231
3	610=<780	384	0.401	0.365	0.422	0.339
4	780=<990	366	0.439	0.401	0.462	0.372
5	990=<1290	379	0.673	0.614	0.708	0.57
6	1290=<1720	376	0.972	0.886	1.02	0.823
7	1720=<2320	382	1.41	1.28	1.48	1.19
8	2320=<3220	387	2.11	1.92	2.22	1.79
9	3220=<4170	382	2.6	2.37	2.74	2.21
10	4170=<	382	3.53	3.22	3.72	2.99
	Outside option		6	5.3	8.1	4.9

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 8: Estimated diversion ratios for four pricing scenarios in group 2

	Size group	Number of stores	Scenario			
			1% price increase by all [✂] stores in group 2	1% price increase by all [✂] stores in group 2	1% price increase by all [✂] stores in group 2	1% price increase by all [✂] stores in group 2
1	280=<430	381	0.169	0.179	0.187	0.169
2	430=<610	376	83.6	81.8	80	83.6
3	610=<780	384	0.361	0.383	0.4	0.363
4	780=<990	366	0.396	0.419	0.439	0.398
5	990=<1290	379	0.607	0.643	0.672	0.609
6	1290=<1720	376	0.876	0.928	0.971	0.88
7	1720=<2320	382	1.27	1.34	1.41	1.27
8	2320=<3220	387	1.9	2.01	2.11	1.91
9	3220=<4170	382	2.35	2.49	2.6	2.36
10	4170=<	382	3.19	3.37	3.53	3.2
	Outside option		5.3	6.5	7.7	5.3

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 9: Estimated diversion ratios for four pricing scenarios in group 4

	Size group	Number of stores	Scenario			
			1% price increase by all [✂] stores in group 4	1% price increase by all [✂] stores in group 4	1% price increase by all [✂] stores in group 4	1% price increase by all [✂] stores in group 4
1	280=<430	381	0.206	0.231	0.239	0.212
2	430=<610	376	0.301	0.338	0.349	0.309
3	610=<780	384	0.442	0.496	0.513	0.453
4	780=<990	366	80.2	72	73.4	79.6
5	990=<1290	379	0.742	0.832	0.861	0.762
6	1290=<1720	376	1.07	1.2	1.24	1.1
7	1720=<2320	382	1.55	1.74	1.8	1.59
8	2320=<3220	387	2.33	2.61	2.7	2.39
9	3220=<4170	382	2.87	3.22	3.33	2.95
10	4170=<	382	3.9	4.37	4.52	4
	Outside option		6.4	3	11.1	6.6

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 10: Estimated diversion ratios for four pricing scenarios in group 5

	Size group	No. of stores	Scenario				
			1% price increase by all [✂] stores in group 5	1% price increase by all [✂] stores in group 5	1% price increase by all [✂] stores in group 5	1% price increase by all [✂] stores in group 5	1% price increase by all [✂] stores in group 5
1	280=<430	381	0.23	0.248	0.263	0.257	0.26
2	430=<610	376	0.335	0.362	0.384	0.374	0.38
3	610=<780	384	0.492	0.531	0.563	0.549	0.558
4	780=<990	366	0.54	0.582	0.618	0.602	0.612
5	990=<1290	379	78.2	76.5	72.9	75.7	75.3
6	1290=<1720	376	1.19	1.29	1.37	1.33	1.35
7	1720=<2320	382	1.73	1.86	1.98	1.93	1.96
8	2320=<3220	387	2.59	2.8	2.97	2.89	2.94
9	3220=<4170	382	3.2	3.45	3.66	3.57	3.62
10	4170=<	382	4.34	4.68	4.97	4.85	4.92
	Outside option		7.2	7.7	10.3	8	8.1

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 11: Estimated diversion ratios for four pricing scenarios in group 7

	Size group	No. of stores	Scenario				
			1% price increase by all [✂] stores in group 7	1% price increase by all [✂] stores in group 7	1% price increase by all [✂] stores in group 7	1% price increase by all [✂] stores in group 7	1% price increase by all [✂] stores in group 7
1	280=<430	381	0.274	0.249	0.225	0.31	0.251
2	430=<610	376	0.399	0.364	0.329	0.453	0.366
3	610=<780	384	0.586	0.534	0.482	0.664	0.537
4	780=<990	366	0.642	0.586	0.529	0.728	0.589
5	990=<1290	379	0.984	0.897	0.81	1.12	0.902
6	1290=<1720	376	1.42	1.3	1.17	1.61	1.3
7	1720=<2320	382	75	77.1	79.2	71.8	77.2
8	2320=<3220	387	3.08	2.81	2.54	3.5	2.83
9	3220=<4170	382	3.81	3.47	3.13	4.31	3.49
10	4170=<	382	5.17	4.71	4.25	5.86	4.74
	Outside option		8.7	8	7.4	9.7	7.8

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 12: Estimated diversion ratios for four pricing scenarios in group 9

	Size group	No. of stores	Scenario			
			1% price increase by all [✂] stores in group 9	1% price increase by all [✂] stores in group 9	1% price increase by all [✂] stores in group 9	1% price increase by all [✂] stores in group 9
1	280=<430	381	0.24	0.23	0.259	0.255
2	430=<610	376	0.351	0.336	0.377	0.372
3	610=<780	384	0.515	0.493	0.554	0.546
4	780=<990	366	0.565	0.541	0.607	0.598
5	990=<1290	379	0.865	0.829	0.93	0.917
6	1290=<1720	376	1.25	1.2	1.34	1.32
7	1720=<2320	382	1.81	1.73	1.94	1.92
8	2320=<3220	387	2.71	2.6	2.92	2.87
9	3220=<4170	382	79.7	80	78.1	78.5
10	4170=<	382	4.54	4.35	4.89	4.81
	Outside option		7.5	7.7	8.1	7.9

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Table 13: Estimated diversion ratios for four pricing scenarios in group 10

	Size group	No. of stores	Scenario			
			1% price increase by all [✂] stores in group 10	1% price increase by all [✂] stores in group 10	1% price increase by all [✂] stores in group 10	1% price increase by all [✂] stores in group 10
1	280=<430	381	0.291	0.196	0.227	0.301
2	430=<610	376	0.425	0.286	0.331	0.439
3	610=<780	384	0.623	0.42	0.486	0.645
4	780=<990	366	0.684	0.46	0.532	0.707
5	990=<1290	379	1.05	0.705	0.816	1.08
6	1290=<1720	376	1.51	1.02	1.18	1.56
7	1720=<2320	382	2.19	1.47	1.7	2.26
8	2320=<3220	387	3.28	2.21	2.56	3.39
9	3220=<4170	382	4.05	2.73	3.15	4.19
10	4170=<	382	76.8	84	82	75.9
	Outside option		9.1	6.5	7.1	9.5

Source: CC Analysis of MPQ responses. Based on nested logit estimation results.

Appendix 3: Store-level price measure

39. Based on responses to the main part questionnaire, we construct a simple measure of store prices based on a basket of 37 generic products. [13] We are to date unable to include more products in the basket, because for many product categories, the responses relate to different products across stores of different chains.[14] We focus on 37 generic product definitions that are unlikely to involve popular brands ("known-value items") and that are stocked by all responding parties (see below for a full list). For example, they include "*White sliced loaf, branded (800g)*"; at [✄] stores, the top-selling brand fitting this description is "Hovis Square Medium White 800g"; at [✄] stores, it is "Hovis Best of Both Medium White 800g". Altogether we find the products listed in response to the 37 generic product definitions to be sufficiently similar for a comparison of prices to be informative regarding price competition between stores of different fascia (after correcting for size or weight differences). Nevertheless, products that fit to the same generic product definition may differ in unobserved quality, which in turn may be reflected in the observed prices. We discuss this issue in more detail in appendix 1.

40. A number of the stores for which we have price data did not stock all of the 37 products.[15] Table 1 summarizes the number of products out of the 37-item basket that are stocked by each store above 280 sq m, separately for each chain. Most stores stock at least 34 of the products in the basket, but a number of stores stocked considerably fewer products. Accordingly, a price measure based on the 37-item basket cannot be calculated directly for more than half of most chains' stores above

[13] Separately for each of 218 product descriptions, we asked parties to "provide data for the "top-selling" products fitting our description, ie those that sold most by value in the week including 20 February 2006 across all your stores". In this request, "top-selling" applies to all stores of the party, e.g. for Tesco we asked for the product that was top-selling across all Tesco fascias including One-Stop.

[14] Firstly, there are brand differences. For example, for the product definition "*Ice cream (500ml to 1 litre) (please state flavour and weight in gram)*", one chain gives the price of a jar of Haagen-Dazs and another gives the price for an own-label product. Secondly, there are differences in product weight or volume, ie one chain has provided the price of a 500g pack whereas another has provided the price of 1kg, say, of tomatoes. It is straightforward to account for these differences; however, this has to be done on a product-by-product and chain-by-chain basis.

280 sq m. To obtain a comparable and informative price measure for a sufficiently large number of stores, we therefore impute a hypothetical price in case a basket product is not stocked in a particular store.

Table 14: Store-level availability of 37-item product basket across chains

Chain	No. of stores (> 280 sq m) in sample	No. of products of the 37-item basket stocked by store		
		Min.	Median	Max.
[✄]	[✄]	0	36	37
		0	32	37
		10	36	37
		0	35	37
		9	33	37
		7	31	36
		26	35	37
		28	36	37
Total	3534	0	34	37

Source: CC analysis of questionnaire responses. A product is defined as not stocked in a store in the week including 20/02/06 if either its shelf price or product-specific revenue is missing or zero for that store in that week.

41. The imputation approach follows the way the U.S. Bureau of Labor Statistics handles missing items in a store that is sampled for its Consumer Price Index.[16] It uses information on non-missing items in that store to calculate a hypothetical price for the missing item such that the basket price can be computed but is unaffected by the imputed value. In other words, since most stores stock some (but few stores all) of the basket products, we use the information on the stocked products to infer a value for the missing product – a value that is neutral to the resulting basket price.

42. In particular, we identify for each product the minimum price posted by a store of the chain. We then calculate for each store the average relative price difference of the stocked basket products, compared to this minimum observed price. For example, if

[15] A product is defined as not stocked in a store in the week including 20/02/06 if either its shelf price or product-specific revenue is missing or zero for that store in that week.
[16] BLS Method Handbook, chapter 17, page 22f.

a [✂] store charges the [✂] minimum price for all its stocked basket products, then the average relative price difference is 0.[17] If the stocked products are on average 10% more expensive than the minimum prices posted by the chain, then the average relative price difference is 10%. The imputed price(s) for the missing product(s) of that store are then simply the chain's minimum price plus the store's relative price difference. In other words, the imputed prices used in calculating the basket do not distort the observed price variation across stores of a chain; but they significantly increase the number of stores that can be included in subsequent analyses. Yet, to avoid imputation based on a low number of observed prices, we only imputed missing prices for stores that stocked at least 9 of the 37 basket products.

43. Our store price measure is then a weighted sum of the store's observed and imputed prices for the basket products (store prices are corrected for differences in product weight or volume across chains). Each product's weight in the basket is then its share in total basket revenue (total revenue generated by sales of the product across all stores, divided by total revenue of all basket products across all stores). Thus the price of a kilogram of bananas tends to have a larger weight in the store price measure, while the price of a kilogram of frozen prawns tends to have a small weight.

44. Table 7 below summarizes the values for our store price measure in terms of deviation from the minimum value observed across all stores. For example, a value 105 indicates that the price measure for the store in question is 5% higher than that for the lowest-price store in the sample.

[17] The same holds for all stores of chains that have a strictly national pricing policy for all products.

Table 15: Summary of store level price measure

Chain	*Statistic*	*Value*	*Chain*	*Statistic*	*Value*
Marks & Spencer	*Average*	[✂]	Tesco	*Average*	[✂]
	Std. deviation			*Std. deviation*	
	Stores covered			*Stores covered*	
Morrisons	*Average*		Waitrose	*Average*	
	Std. deviation			*Std. deviation*	
	Stores covered			*Stores covered*	
Asda	*Average*		Sainsbury's	*Average*	
	Std. deviation			*Std. dev.*	
	Stores covered			*Stores covered*	
Co-op Main	*Average*		Somerfield	*Average*	
	Std. deviation			*Std. deviation*	
	Stores covered			*Stores covered*	
			All stores	*Average*	122
				Stores covered	3526

Source: CC analysis of questionnaire responses. Store price measure is re-scaled such that 100 represents the value for the lowest-price store (according to the measure) in the sample.

45. Consistent with a national pricing strategy, the price measure does not vary across [✂] and [✂] stores. For other chains, prices vary to some extent across stores. For [✂] stores, most of this variance is a result of price variance across the different [✂] fascias [✂].

Table 16: List of 37 generic product definitions

Our reference	**Product definition**
priceprod4	white sliced loaf, branded (800g)
priceprod5	wholemeal sliced loaf, branded (800g)
priceprod6	flour, self-raising (1.5kg)
priceprod7	dry spaghetti or pasta (500g)
priceprod19	home killed beef, lean mince (per kg)
priceprod20	home killed beef, rump steak (per kg)
priceprod21	home killed beef, topside (per kg)
priceprod23	home killed beef, braising steak (per kg)
priceprod24	home killed lamb, loin chops with bone (per kg)
priceprod28	home killed pork, loin chops with bone (per kg)
priceprod30	bacon, gammon (per kg)

priceprod31	bacon, back (per kg)
priceprod47	frozen prawns, packed (per kg)
priceprod67	fresh single cream (284ml)
priceprod70	fruit squash orange (1 litre)
priceprod71	pure orange juice (1 litre carton)
priceprod73	lemonade (2 litre bottle)
priceprod82	sugar (granulated) white (per kg)
priceprod93	potatoes, new, loose (per kg)
priceprod100	fresh veg, cauliflower (each)
priceprod101	fresh veg, cucumber (whole)
priceprod102	fresh veg, lettuce, iceberg (each)
priceprod103	fresh veg, tomatoes (per kg)
priceprod105	fresh veg, sprouts (per kg)
priceprod106	fresh veg, carrots (per kg)
priceprod108	fresh veg, mushrooms (per kg)
priceprod109	fresh veg, organic carrots (per kg)
priceprod111	fresh veg, lettuce, round (each)
priceprod118	avocado pear (each)
priceprod122	apples, cooking (per kg)
priceprod123	apples, dessert (per kg)
priceprod125	bananas (per kg)
priceprod126	strawberries (per kg)
priceprod127	grapes (per kg)
priceprod184	bleach (750ml bottle)
priceprod191	dog food, can (390-400gm)
priceprod192	cat food, can (390-400gm)