

Demand estimation from TNS consumer choice data

Introduction

1. This appendix presents the results of our empirical estimation of demand for grocery stores. Using data collected by TNS from 11,382 UK households, we estimate an econometric model that explains consumer choice of grocery store. We use the results of this econometric model to predict consumers' reactions when faced with a small but significant price increase. These predictions of consumer substitution patterns are informative for our assessment of market definition.
2. The results suggest that: (a) shoppers view stores operated by the four largest grocery retailers as substitutes, and that they also view Waitrose and Somerfield stores as substitutes to the stores of the four largest grocery retailers; (b) shoppers buying at large stores are far more likely to substitute towards larger stores than smaller stores, implying that large grocery stores are the main competitive constraint for other large stores; and (c) consumer substitution is local, that is, shoppers who switch in response to a small but significant price rise will switch to stores located close to home.

The data and the econometric model

3. We use data from TNS that contains information on the shopping trips of 11,382 households living in the UK for the four-week period 9 October to 5 November 2006. The dataset also provides information on some characteristics of each household, such as the social group it belongs to. Each household reports on each shopping trip, using a home scanner, recording the date and the grocery store visited, total spend and an itemized list of grocery items purchased. The dataset provided to the CC includes all shopping trips to outlets of six fascias: Asda, Morrisons, Sainsbury's,

Somerfield, Tesco and Waitrose. These retailers combined make around 67 per cent of all UK grocery sales made by grocery retailers.

4. The dataset contains all shopping trips for these households irrespective of their size: grocery expenditure totals less than £5 for some shopping trips, and more than £50 for many others. Depending on the amount they spend and the type of shopping mission that they do on any given trip, consumers may react differently to a price increase. Therefore, we have constructed a sample that contains one 'major' shopping trip for each household. We defined major shopping trips as those whose expenditure accounted for at least 60 per cent of a household's weekly expenditure on groceries as reported in the sample. We further constructed another random sample based on 'minor' shopping trips. Those are made up of shopping trips whose expenditure represented less than 60 per cent of a household's weekly expenditure on groceries. We will estimate our model on both samples separately and will compare the results.

5. During this investigation, we have collected a comprehensive data set of many UK groceries stores. This allows us to determine for each household in the TNS dataset their choice of local grocery stores. Based on the existing road network, we computed the drive-time between each consumer's home and each local grocery store. This allowed us to determine the geographic scope of demand-substitution in more realistic terms than using a more simplistic straight line. For all these grocery stores, we also have information on characteristics, such as store size, which we consider to be important when evaluating the choices of consumers. We also collected price information on a selection of branded and basic grocery goods during one week in 2006. For each store, we constructed a price measure which should reflect the price level of a basket of major goods for that store.

6. We apply standard econometric methods that are often employed to estimate demand in differentiated product industries with household level data.¹ We treat each household as an individual consumer who must choose one grocery store out of all stores that are within reasonable reach of their home.² Based on the observed choices made by each household, the model estimates the probability that a consumer purchases their groceries from a specific local grocery store. This probability estimate is based on the household's and stores' characteristics as well as on the drive-time between each store and the household's home. Using the estimated relationship between choice and observed characteristics, we check that the model's predictions are in line with the actual choice in the sample. We can then predict the extent of consumer switching following a change in price or another store attribute, which provide information of consumer substitution patterns.³
7. The results of our demand estimation cannot be readily used in a formal SSNIP test. One reason is that the demand model explains consumer choice of grocery store, but it does not model consumer expenditure.⁴ For example, following a price increase, consumers could either change their choice of local store, or reduce their spending on groceries by purchasing cheaper items. Hence, information on the number of households that change their choice of local store does not directly translate into an amount of lost revenue for a store, which is needed for a formal SSNIP analysis. Furthermore, because of data limitations we do not have information on consumer

¹We estimate a mixed multinomial logit (MMNL) model which belongs to the family of discrete choice models. In the technical annex we provide further technical information on this class of models.

²In general, we consider all stores within 20 minutes of a consumer's home. If this choice set contains less than 30 stores then we extend the radius up to 90 minutes.

³Tesco submitted the results of an econometric analysis using a simple conditional logit model based on 186,000 actual shopping trips from the TNS Superpanel data. Tesco used the estimation results of the model to translate average consumer preferences for some store characteristics into drive-time equivalents. It submitted that when looking at size alone, the results suggest that customers place extra weight on stores above 280 sq metres compared with stores smaller than this, but that there is no clear distinction between stores above 280 sq metres. Moreover, over and above the size differences captured by different fascia, Tesco said that the results showed that consumers do not place further value on store size (either in absolute terms or relative to the largest store in the area) for stores above 280 sq metres. Tesco considered that this result from its analysis was relevant to product market definition since it did not support an absolute or relative store size cut-off (other than above 280 sq metres), but only a fascia distinction.

⁴The model does not predict a particular choice for an individual but the probability of shopping at the different stores in his choice set. A change in choice thus reflects a change in probability of shopping at the different stores. In the aggregate, over all consumers, this translates into market shares for different groups of stores, for example different fascias, and a change can thus be interpreted as consumer switching.

shopping at grocery stores that do not belong to the six fascias included in the dataset.⁵ We only present the choice of grocery store conditional on consumers choosing stores from the six main grocery retailers in the UK. This affects how the model predicts reactions to a change in store characteristics as the option to select an ‘outside alternative’ is not present.⁶ The demand estimates are, nonetheless, informative on consumer switching across different groups of stores and are therefore relevant to our consideration of market definition.

The model’s predictions

8. Using the econometric estimates of the demand model, we can predict consumers’ reaction to a small but significant price increase.⁷ It should be noted that the change in price corresponds to a change in the prices of a selection of important products from different product categories (as given by our price measure) sold by this store or group of stores. In this scenario, consumer reactions will be greater than when the price of one product or a small subset of products sold at a store is increased.

9. Furthermore, it is important to note that the nature of the data and the model allows us to assess a consumer’s change in grocery store choice. However, we do not directly assess the resulting loss in volume sales following a price increase. In particular, the model predicts the proportion of consumers who switch to different competing fascias and different store sizes. The model’s predictions also provide evidence on the geographic scope of consumer switching.

⁵For its estimation of a conditional logit, Tesco uses data from TNS. In that analysis it refers to a greater range of fascias than we included in this model. [X]

⁶We expect this mostly to affect the absolute or aggregate sizes of the predicted changes and not the relative impact on different groups of stores.

⁷In a discrete choice model the coefficient estimates represent the impact of a certain variable on consumer’s utility. To assess the impact on market outcome we therefore compute the extent of aggregate consumer switching following a small but significant price increase and present these derived results instead. The coefficient estimates are provided in the technical annex.

Consumer switching across fascias

10. First, we predict the change in household choice of grocery store based on a 2 and a 5 per cent price increase of one fascia, the resulting change in market share for this fascia and how much competing fascias benefit from this price increase. The results for changes in market share for both major and minor shopping trips are reproduced in Table 1. First, shoppers are more likely to change their choice when they undertake a major shopping trip. For example, when Asda increases the price of all of its products by 2 per cent and 5 per cent, its share of consumers would decline by 18.4 and 41.9 per cent respectively on our analysis of major shopping trips. This corresponds to an own-price elasticity for Asda of around 8 to 9 for major trips.⁸ However, for minor trips, Asda's share would be reduced by only 11.4 and 27.0 per cent, implying an own-price elasticity of around 5 to 6. Second, we note that regardless of the type of shopping trip, Waitrose and Somerfield are predicted to lose proportionally more consumers from a price increase than the other fascias. For example, for a 2 per cent price increase, their share of consumers will decline by more than 30 per cent for major trips, although the own-price elasticity is less sensitive for minor trips.
11. Generally, the estimates of consumer reactions to price changes indicate that grocery retailers face elastic demand, and our sample of major trips appears even more price sensitive. [✂]

⁸These implied price elasticities are sensitive to the size of the price increase. If we compute them from the reaction to a 2 per cent price increase the corresponding value is -9.2 and the reaction to a 5 per cent price increase results in an elasticity of -8.4.

TABLE 1 Percentage change in the share of consumers

<i>Fascia</i>	<i>per cent</i>			
	<i>Major trips</i>		<i>Minor trips</i>	
	<i>2% price increase</i>	<i>5% price increase</i>	<i>2% price increase</i>	<i>5% price increase</i>
Asda	-18.4	-41.9	-11.4	-27.0
Morrisons	-20.8	-45.6	-12.2	-28.5
Sainsbury's	-24.1	-51.5	-14.3	-32.9
Somerfield	-31.1	-60.1	-18.3	-40.1
Tesco	-16.5	-38.5	-10.6	-25.4
Waitrose	-32.6	-63.9	-19.2	-42.2

Source: CC analysis.

12. Next, we analyse which fascia households switch to. The model predicts how each grocery chain benefits from a rival's small price increase. The results of this analysis, based on major shopping trips, are summarized in Table 2. For each fascia, Table 2 shows the percentage change in market share following a 2 and 5 per cent price increase of a rival. For example, when all Asda grocery outlets increase their price by 5 per cent we can read across the row to see that Morrisons' share of households increases by 15.42 per cent, Sainsbury's by 13.33 per cent, Tesco's by 12.50 per cent, Somerfield's by 11.75 per cent, while Waitrose's increases by only 7.27 per cent. Morrisons, and to a lesser extent Sainsbury's, Tesco and Somerfield, gain from an Asda price increase more than Waitrose but in general the differences are small. Also, when reading the results down a single column we can see that Waitrose gains the most from a price increase by Tesco (11.99 per cent for a 2 per cent price increase) and Sainsbury's (8.17 per cent for a 2 per cent price increase) but less from a price increase by Asda, Morrisons or Somerfield.

TABLE 2 **Percentage change in the share of households buying from different fascia following a price increase of a rival, major trips**

	<i>per cent</i>					
	<i>Asda</i>	<i>Morrisons</i>	<i>Sainsbury's</i>	<i>Somerfield</i>	<i>Tesco</i>	<i>Waitrose</i>
<i>2% price increase</i>						
Asda	-18.36	6.69	5.83	5.08	5.52	3.24
Morrisons	4.41	-20.82	3.66	4.28	3.65	2.84
Sainsbury's	4.65	4.41	-24.05	5.57	5.40	8.17
Somerfield	1.18	1.48	1.57	-31.06	1.35	1.89
Tesco	8.98	8.99	11.00	9.39	-16.52	11.99
Waitrose	0.33	0.43	0.98	0.84	0.72	-32.61
<i>5% price increase</i>						
Asda	-41.91	15.42	13.33	11.75	12.50	7.27
Morrisons	9.56	-45.58	8.03	9.98	7.97	6.29
Sainsbury's	9.78	9.37	-51.48	12.48	11.58	18.42
Somerfield	2.26	2.90	3.01	-60.12	2.63	3.68
Tesco	20.59	20.96	25.95	22.53	-38.54	28.94
Waitrose	0.63	0.85	1.91	1.76	1.40	-63.89

Source: CC analysis.

13. Table 3 reproduces results using minor shopping trips. The pattern is not vastly different from that of major trips, although the differences in numbers for the different beneficiaries of a fascia's price increase are small. Thus, for minor trips the fascias in the sample closely compete.

TABLE 3 **Percentage change in the share of households buying from different fascia following a price increase of a rival, minor trips**

	<i>per cent</i>					
	<i>Asda</i>	<i>Morrisons</i>	<i>Sainsbury's</i>	<i>Somerfield</i>	<i>Tesco</i>	<i>Waitrose</i>
<i>2% price increase</i>						
Asda	-11.41	3.23	2.85	2.69	2.70	1.73
Morrisons	2.78	-12.18	2.27	2.42	2.32	1.62
Sainsbury's	3.11	2.85	-14.27	3.40	3.45	5.03
Somerfield	2.15	2.24	2.47	-18.33	2.25	2.01
Tesco	4.33	4.30	5.08	4.52	-10.66	5.31
Waitrose	0.46	0.50	1.20	0.67	0.87	-19.16
<i>5% price increase</i>						
Asda	-26.98	7.66	6.74	6.38	6.38	4.03
Morrisons	6.49	-28.48	5.29	5.73	5.42	3.77
Sainsbury's	7.09	6.55	-32.95	7.95	7.98	11.87
Somerfield	4.68	4.93	5.37	-40.14	4.95	4.41
Tesco	10.24	10.26	12.14	10.89	-25.43	12.77
Waitrose	0.99	1.09	2.63	1.49	1.93	-42.16

Source: CC analysis.

14. We conclude that shoppers' propensity to switch following a small but significant price increase is higher for larger shopping trips than for smaller ones. Generally,

Waitrose and Somerfield stand to lose more from a price increase than the four largest retailers. Finally, while there are smaller differences in the competitive constraints that the different fascias exert on each other, all fascias in our sample appear to compete closely.

Consumer switching and store size

15. The estimation results allow us to determine how the share of consumers buying from large stores changes following a small but significant price increase of an important number of products at large stores of a certain fascia. In particular, we analyse the proportion of those shoppers who switch to other large competitor stores.

16. As already shown above, the model predicts that after raising its price a grocery retail chain will lose consumers. In Tables 4 and 5 we present for each fascia the share of households buying from large stores who switch to a rival grocery store. We use two different definitions of large stores based on grocery net sales area (greater than 1,400 sq metres and 2,000 sq metres). The results are very similar in size to those presented in Table 1. In general, they indicate that a substantial proportion of households would switch following a small but significant price increase. The difference in consumer price sensitivity between large stores greater than 1,400 sq metres and those greater than 2,000 sq metres appears negligible. Again, fewer households change their choice for their minor trips, otherwise the differences are small between the two samples.

TABLE 4 Percentage change in the share of households buying from large stores, major trips

Fascia	per cent			
	1,400 sq m 2% price	1,400 sq m 5% price	2,000 sq m 2% price	2,000 sq m 5% price
Asda	-18.4	-41.9	-18.4	-41.9
Morrisons	-20.9	-45.8	-21.8	-47.3
Sainsbury's	-24.5	-52.2	-25.0	-52.9
Somerfield	-34.3	-65.7	N/A	N/A
Tesco	-17.4	-40.1	-18.2	-41.5
Waitrose	-32.6	-63.8	-33.3	-65.0

Source: CC analysis.

Notes:

1. We are not reporting results for Somerfield stores above 2,000 sq metres as there are very few of them in the sample and results might be due to computational inaccuracies. Equally, the results for Somerfield stores above 1,400 sq metres and for Waitrose stores above 1,400 sq metres should be interpreted with caution.
2. N/A = not available.

TABLE 5 Percentage change in the share of households buying from large stores, minor trips

Fascia	per cent			
	1,400 sq m 2% price	1,400 sq m 5% price	2,000 sq m 2% price	2,000 sq m 5% price
Asda	-11.40	-26.97	-11.42	-26.96
Morrisons	-12.31	-28.75	-12.65	-29.48
Sainsbury's	-14.74	-33.84	-15.21	-34.75
Somerfield	-20.95	-44.59	-25.00	-50.00
Tesco	-11.36	-26.90	-11.90	-28.00
Waitrose	-19.23	-42.31	-19.54	-43.68

Source: CC analysis.

Note: We are not reporting results for Somerfield stores above 2,000 sq metres as there are very few of them in the sample and results might be due to computational inaccuracies. Equally, the results for Somerfield stores above 1,400 sq metres and for Waitrose stores above 1,400 sq metres should be interpreted with caution.

17. Next, we analyse whether shoppers which are lost by large stores (greater than 1,400 sq metres and greater than 2,000 sq metres) following a price increase would change to other large stores or would equally consider smaller size stores as an alternative to shopping at large stores. In particular, we analyse the proportion of households buying from large stores that would switch to other rival large stores. Table 6 presents these diversion ratios for major trips.

18. Regardless of the type of shopping, the results show that the vast part of the share of shoppers which are lost will be gained by other large stores. That proportion is higher when the store is larger than 1,400 sq metres. For example, for a major trip with a

5 per cent price increase, 90 per cent of households lost by Asda stores larger than 1,400 sq metres would switch to competitor stores whose size is larger than 1,400 sq metres. This figure declines to around 81 per cent when the large store is defined to have a net sales area greater than 2,000 sq metres. This differential in results indicates that a proportion of households substitute shopping at a store larger than 2,000 sq metres with stores shopping at stores between 1,400 and 2,000 sq metres.

19. The results show that the proportion substituting to other similar sized large stores is not as significant for minor trips, yet more than 75 per cent of marginal consumers would still switch to other large stores larger than 1,400 sq metres. This implies that customers of large stores tend to switch to other large stores, although this relationship is not as strong for households undertaking a minor shopping trip.

TABLE 6 Proportion of marginal shoppers buying at large stores switching to other large stores, 5 per cent price increase

Fascia	<i>per cent</i>			
	<i>Major trips</i>		<i>Minor trips</i>	
	<i>Proportion to stores larger than 1,400 sq m</i>	<i>Proportion to stores larger than 2,000 sq m</i>	<i>Proportion to stores larger than 1,400 sq m</i>	<i>Proportion to stores larger than 2,000 sq m</i>
Asda	90.0	80.8	80.2	69.0
Morrisons	87.6	81.1	78.9	71.3
Sainsbury's	87.2	76.7	76.5	64.0
Somerfield	88.6	N/A	81.8	N/A
Tesco	86.4	75.5	76.4	64.1
Waitrose	85.2	76.9	77.8	68.4

Source: CC analysis

Notes:

1. We are not reporting results for Somerfield stores above 2,000 sq metres as there are very few of them in the sample and results might be due to computational inaccuracies. Equally, the results for Somerfield stores above 1,400 sq metres and for Waitrose stores above 1,400 sq metres should be interpreted with caution.
2. N/A = not available.

20. Overall, these results show that households consider that large stores are the next best alternative to other large stores. We conclude that the main competitive constraint faced by a store larger 1,400 sq metres is another store larger than 1,400 sq metres.

Geographic dimension of demand substitution

21. The results of the demand estimation also provide evidence that consumer substitution is essentially local. The econometric results can be used to assess empirically the extent to which consumers will choose more distant stores following a small but significant price increase. The results show that most shoppers buying from stores close to home will not consider stores that are more distant as a suitable substitute.

22. Table 7 presents results based on the model's predictions. Following a small but significant price increase by nearby stores, few consumers are willing to incur higher travelling costs to buy from stores farther away. For example, if all stores within 5 minutes of a household's home increase their prices by 2 per cent, the proportion of shoppers carrying major trips at those stores declines by 13.5 per cent. Naturally, that proportion is reduced by more, 32.4 per cent, for a 5 per cent price increase. However, as we increase the drive-time between grocery outlets and a consumer's home, that proportion becomes much smaller indicating that shoppers will not view farther away stores as a credible alternative.

23. We have evaluated price increases of all stores within 10, 15 or 20 minutes of a consumer. The table shows that as drive-times increase, a 2 or 5 per cent price increase will cause relatively less household switching. For example, the proportion of shoppers going to stores within 10 minutes of their house for a major trip declines by 24.3 per cent if these stores increase their prices by 5 per cent. The corresponding own-price elasticity is 4.9. In contrast, if all stores within 15 minutes of their house increase price, the proportion of those shopping within 15 minutes declines by only 13.5 per cent. The corresponding elasticity is -2.7 . This shows that as drive-time increases, most households buying from stores close to home will not consider stores farther away from home as a substitute.

24. The results for consumers undertaking minor shopping trips show the same pattern, yet the propensity of consumers not to switch to stores further away is even stronger. Following a 5 per cent price increase, the proportion of households buying from stores within 5 minutes of home will decline by 19.3 per cent. This reduction reduces quickly as drive-time increases.

TABLE 7 Prediction of consumer switching towards more or less distant stores following a price increase by nearby stores, major trips

Price increase by stores within	<i>per cent</i>			
	Change in consumers, switching to more distant stores for major trips after a		Change in consumers, switching to more distant stores for minor trips after a	
	2% price increase	5% price increase	2% price increase	5% price increase
5 minutes	-13.5	-32.4	-7.8	-19.3
10 minutes	-9.4	-24.3	-4.7	-12.4
15 minutes	-4.7	-13.5	-2.0	-5.6

Source: CC analysis.

25. The results in the technical annex show that the majority of households that switch, switch to stores within the next closest drive-time band. These results and the previous discussion indicate that households are very sensitive to drive-time and are unlikely to switch to more distant stores following a small but significant price increase.

Detailed results from the estimation of a discrete choice model

1. This technical annex presents more detailed results from the estimation of a discrete choice model using micro-level data.

Demand model

2. We use a discrete choice framework to estimate consumer choice of grocery outlets. We use a demand model that belongs to the class of MMNL models of discrete choice.¹ Models of discrete choice are used on data where we observe consumers' choices among a number of alternatives. If there is more than one choice to make (in this context, more than two grocery outlets within the reach of a household) the models are called *multinomial*. These models assume that a consumer will select the alternative that provides the highest utility level.
3. Making further assumptions on the structure of the decision problem, it is possible to derive theoretical 'choice probabilities' for each consumer and each available alternative which depend on some unknown parameters. That is, given specific values for these parameters, the theoretical model postulates choice probabilities depending on the characteristics of the consumer and the alternatives. The estimation algorithm chooses values for these parameters so that the theoretical choice probabilities for all consumers and all alternatives predict the actual distribution of observed choices as closely as possible. The parameter estimates allow us, in a second step, to compute certain characteristics of demand, for example price elasticities, and consumers' reaction to changes in available choices.

¹The mixed-logit model, as shown by McFadden and Train (2000), can approximate any random utility model under mild regularity conditions.

4. In the standard multinomial logit model (MNL) the (indirect) utility of consumer i when shopping at store j , which is one of the J_i alternative stores in her choice set, is given by:

$$u_{ij} = x_j' \theta_x - \theta_p p_j - \theta_{dist} dist_{ij} + \varepsilon_{ij},$$

where x_j is a vector of store characteristics, p_j is the price measure of the store and $dist_{ij}$ is the drive-time between the store and the household. The unobserved part of consumer utility is given by ε_{ij} . In our case, this represents unobserved store and household taste characteristics. This error term is assumed to have an extreme value type I distribution and as a result the differences of random characteristics between any two choices are distributed logistically, hence the name *logit* model.

5. Each household compares all available alternatives and chooses the grocery store that provides the highest level of utility: $u_{ij} > u_{ik} \forall k \neq j; k, j \in J_i$, where J_i represents the choice set of household i . Because some components of the utility function are unobserved—we do not observe all aspects of household i 's utility function—we can only predict the probability that each alternative will be selected. The mathematical expression for this probability depends in part on the specific distribution of the unknown component of utility. When the unobserved portion of utility is assumed to be an independently and identically distributed type I extreme value, then the probability of each alternative has a closed-form solution (the standard logit choice probability) which is given by:

Equation 1

$$\begin{aligned} P_{ij}(x, p, dist_i; \theta_x, \theta_p, \theta_{dist}) &= \Pr(u_{ij} > u_{ik} \forall k \neq j; k, j \in J_i) \\ &= \Pr(\varepsilon_{ij} - \varepsilon_{ik} > (x_k' - x_j') \theta_x - \theta_p (p_k - p_j) - \theta_{dist} (dist_{ik} - dist_{ij}) \forall k \neq j; k, j \in J_i) \\ &= \frac{\exp(x_j' \theta_x - \theta_p p_j - \theta_{dist} dist_{ij})}{\sum_{k \in J_i} \exp(x_k' \theta_x - \theta_p p_k - \theta_{dist} dist_{ik})} \end{aligned}$$

6. MNL models have well-known shortcomings. Implausible substitution patterns can occur since choices between two alternatives are not allowed to be influenced by characteristics of other alternatives in the choice set (independence of irrelevant alternatives (IIA) property). Consider, for example, that a household has a choice between a Morrisons and a Waitrose and that our discrete choice model attributes a probability of $\frac{1}{2}$ of choosing either of them. Now assume an Asda store is introduced in the household's choice set. A standard logit model would assume that the household selects Morrisons, Waitrose or Asda each with probability of $\frac{1}{3}$ keeping constant the odds of selecting Morrisons over Waitrose. If Morrisons and Asda tend to be viewed as closer substitute, this will not be the case. More likely, the probability of choosing the Waitrose would then remain at about $\frac{1}{2}$ while the household would choose either Tesco or Asda with probability $\frac{1}{4}$ (or something close to it).

7. MMNL models overcome this restriction. Unlike the standard logit model, households are allowed to have differing tastes for observed store characteristics. As a result, some households might put a higher value on being geographically close to their grocery outlets than others. In this case, these households may not substitute to stores located much further away compared with other consumers who do not mind travelling for their grocery shopping. The formula for the utility is the same as in the MNL, except that we consider two of the parameters to be random now, θ_p and θ_{dist} , that is, they can take different values across households. We can then let households differ in their price sensitivity and incur differing disutility of travelling to grocery stores. The computation of the choice probabilities follows the same procedure as above. Each household, knowing their value of θ_p and θ_{dist} , chooses the grocery store that provides the highest level of utility.

8. Because we do not know the values of θ_p and θ_{dist} , we have to build an expectation over these parameters to predict choice probabilities:

Equation 2

$$\begin{aligned} P_{ij}(x, p, dist_j, z_i; \theta_x, \beta) &= E_{\theta_p, \theta_{dist}} [P_{ij}(x, p, dist_j; \theta_x, \theta_p, \theta_{dist}) | z_i, \beta] \\ &= \int_{\theta_{dist}} \int_{\theta_p} P_{ij}(x, p, dist_j; \theta_x, \theta_p, \theta_{dist}) dG(\theta_p, \theta_{dist}; z_i, \beta) \\ &= \int_{\theta_{dist}} \int_{\theta_p} \frac{\exp(x_j' \theta_x - \theta_p p_j - \theta_{dist} dist_{ij})}{\sum_{k \in J_i} \exp(x_k' \theta_x - \theta_p p_k - \theta_{dist} dist_{ik})} dG(\theta_p, \theta_{dist}; z_i, \beta) \end{aligned}$$

The expectation is build over the specific distribution $G(\theta_p, \theta_{dist}; z_i, \beta)$ which depends on the household's characteristics z_i and an unknown parameter β which will be estimated (instead of θ_p, θ_{dist}). We assume this function is jointly log-normal. β thus includes parameters for the mean and standard deviations of distance and price, as well as the covariance between price and distance. The mean will be a linear function of the consumer specific characteristics household size, a dummy for social group DE and the number of cars per household and also contains an intercept.

9. In the MMNL model, the cross-price elasticities depend also on the characteristics of other alternatives. This is because elasticities depend on choice probabilities which on their part represent an expectation over different household types. Households who value proximity are more likely to substitute grocery stores that are not too far from home while those who do not are willing to travel farther. The IIA assumption is thus overcome.

Estimation methodology

10. The choice probabilities in Equation 2 depend on unknown parameters. In this section we describe how these parameters are estimated from the data. The main idea behind the estimation methodology is that these parameters are selected so that the predicted choice probabilities match the observed choices as closely as possible. The probability of observing the combination of choices in our sample is equivalent to the probability that each of the consumers in our dataset chooses the observed alternative. As consumers are independent from each other this joint probability is

given by the product of the individual choice probabilities as shown in Equation 1 and Equation 2, respectively. Using the method of Maximum Likelihood we maximize this joint probability (or alternatively the logarithm of it) with respect to the unknown parameters:

$$MNL: [\hat{\theta}_x, \hat{\theta}_p, \hat{\theta}_{dist}] = \operatorname{argmax}_{\theta_x, \theta_p, \theta_{dist}} \sum_{i=1}^n \sum_{j \in J_i} d_{ij} \ln(P_{ij}(x, p, dist_i; \theta_x, \theta_p, \theta_{dist}))$$

and

$$MMNL: [\hat{\theta}_x, \hat{\beta}] = \operatorname{argmax}_{\theta_x, \beta} \sum_{i=1}^n \sum_{j \in J_i} d_{ij} \ln(P_{ij}(x, p, dist_i, z_i; \theta_x, \beta))$$

where d_{ij} is an indicator representing whether the alternative was chosen ($d_{ij} = 1$) or not ($d_{ij} = 0$).

11. The computation of choice probability for the MMNL model involves a complicated integral that is not analytically tractable. We will first approximate this integral by simulation. Then we obtain our parameter estimates by maximizing the simulated likelihood function. That is, in the above formula for the likelihood we replace the analytical choice probabilities with the simulated ones as given below, and optimize over this 'simulated likelihood function'. Simulation of the choice probability of consumer i can be carried out as follows: for a given parameter vector β and consumer characteristics z_i , we randomly draw θ_p and θ_{dist} from the distribution $G(\theta_p, \theta_{dist}; z_i, \beta)$. For each of these random draws $\tilde{\theta}_{p,s}$ and $\tilde{\theta}_{dist,s}$, $s=1 \dots S$, we compute the corresponding choice probability for the selected alternative. Next we compute the mean probability over all S draws, and this gives the simulated choice probability for consumer i .

$$\tilde{P}_{ij,S}(x, p, dist_i, z_i; \theta_x, \beta) = \frac{1}{S} \sum_{s=1}^S P_{ij}(x, p, dist_i; \theta_x, \tilde{\theta}_{p,s}, \tilde{\theta}_{dist,s})$$

Data

12. The demand model is estimated using data from a TNS panel comprising 11,382 UK households that regularly report on their grocery shopping trips. Each household in the panel records the date and the grocery store visited as well as the total amount spent and a list of grocery items purchased on each of its grocery trips using a home scanner. TNS additionally collects socio-demographic information for these households such as residential location, household size, social grade and car ownership.

13. The CC used a sample of shopping trips recorded during a four-week period in 2006 (9 October to 5 November). For each consumer, the decision to shop at a certain grocery store and the amount spent on each trip is clearly correlated across shopping trips. For example, a consumer who spent a large amount on groceries one day is less likely to buy a large amount the following day. On the other hand, if they have not shopped for groceries for a while, they will be likely to do so within the next few days. To abstract from such dynamic considerations in the household's decision problem we will concentrate on one trip per household.²

14. Not all shopping trips are equivalent. Many households undertake one major shopping trip a week, while others frequently visit one or more grocery stores during a week. Because consumer price sensitivity may be different depending on the nature of the shopping trip, we split the data into major shopping trips considered to be those in which expenditure represents at least 60 per cent of household average weekly spend. Those trips where less than 60 per cent of the average weekly spend occurs, are termed minor shopping trips. From the sample of 'major' shopping trips, we randomly draw one trip per consumer. We perform the same exercise for minor

²To accommodate this dynamic aspect of consumer behaviour, we would have to allow unobserved factors to be correlated overtime. This presents some additional difficulties for the estimation of the econometric model.

shopping trips. The following summary statistics provide information on the two samples.

15. Table 1 reports summary statistics for the socio-demographic variables included in the sample. A little more than 50 per cent of households have either one or two members and about 85 per cent of them own at least one car. We also note that social groups D and E represent about 30 per cent of the sample while the rest belong to either the groups A and B or to C1 and C2.³

TABLE 1 Summary statistics of random sample of major shopping trips in TNS sample data

Major trips			Minor trips		
HH size	Cars	Social grade	HH size	Cars	Social grade
%	%	%	%	%	%
1	20.77	0	15.56	A, B	10.7
2	35.01	1	51.73	C1, C2	59.0
3	16.71	2	28.32	D, E	30.3
4	18.21	3	3.42		
5	6.85	4	0.72		
>=6	2.45	5	0.15		
		6	0.10		

Source: Sample from the TNS Consumer Panel

16. Table 2 presents the distribution of shopping spend and the drive-time between household and grocery outlets. As expected, households spend on average considerably less on their minor trips than on their major trips. Shopping spends vary greatly, with the top 10 per cent of households spending above £92.22 on major trips and £27.13 on minor trips. In contrast, 10 per cent of households on the other hand spend less than £13.83 on major trips and less than £2.12 on minor trips. The median major shopping trip represents £42.49 while the median minor shopping trip represents £9.20. Using mapping software, the CC also computes the drive-time between a household and a store's location (reported in minutes) and is included in this demand model to explain consumer selection of local stores. Our analysis shows

³The classification follows the National Statistics Socio-economic Classification provided by the ONS. It is an occupationally-based classification but has rules to provide coverage of the whole adult. For further information see: www.statistics.gov.uk/methods_quality/ns_sec.

that households tend to shop closer to home on minor trips. The median consumer, for example, shops within 8 minutes from where they live for major trips and within 6 minutes for minor trips. Further, 11 per cent of households shop within 1 minute and only 10 per cent shop further away than 17 to 18 minutes.

TABLE 2 **Distribution of shopping spend and drive-time**

Quantile %	Major trips		Minor trips	
	Spend £	Drive-time mins	Spend £	Drive-time mins
Min	0.49	1	0.10	1
10	13.83	1	2.12	1
25	24.63	5	4.60	3
50	42.49	8	9.20	6
75	66.08	13	16.87	11
90	92.22	18	27.13	17
Max	829.00	88	99.32	87

Source: Sample from the TNS Consumer Panel

17. The choice data provided to the CC contains only those stores for which TNS knew the location of the store. Where we know the location of the store we can then compute drive-time between a household and these stores. [X]
18. The decision made by a household on where to shop is influenced by the choice that is available to that particular household, that is, stores within reasonable reach. We identify stores that can be reached by each of the households in the TNS data. We assume that households have a non-zero probability of visiting all grocery stores within 20 minutes' drive-time of their location (only 6 per cent of households actually visited outlets beyond this distance). These grocery stores form the consumer's choice set. However, if the choice set comprises fewer than 30 stores, we extend the drive-time to up to 90 minutes. Table 3 shows which fascias are available to consumers and which ones they actually chose. For example, while nearly 25 per cent of consumers have a Somerfield within reach, only 4.25 per cent choose it for their major shopping trips. In general, the actual choices made more closely represent the available alternatives for minor trips

TABLE 3 Available fascias and consumer choices

<i>Fascia</i>	<i>In consumer's choice set</i>	<i>per cent</i>	
		<i>Consumer's choice Major trips</i>	<i>Minor trips</i>
Asda	12.29	23.85	19.71
Morrisons	12.34	15.72	16.48
Sainsbury's	19.46	17.38	18.82
Somerfield	24.56	4.25	10.96
Tesco	25.11	36.91	30.22
Waitrose	6.24	1.89	3.81

Source: Sample from the TNS Consumer Panel and data collected from main parties to the inquiry.

19. The decision for where to shop is also influenced by a store's characteristics. For example, the size of a store or the presence of other facilities such as a petrol forecourt or an ATM will affect a consumer's decision. During the inquiry we collected data on stores and their characteristics from the main grocery retailers. For these stores we report the existence of a petrol station, an ATM, cafeteria/restaurant or toilets and fascia and store size.
20. Finally we include a price measure. The measure is constructed from price information from the main parties for a week in February 2006. We compute a weighted average across a selection of basic non-branded and branded goods which are sold by all retailers. Further details on the constructions of this price measure are provided in the supplement. The price information does not strictly match the sample period over which the TNS data is reported. However, we posit that the cross-section variation between fascia and format would not be so different as to be relevant for the TNS panel. Table 4 reports summary statistics on the grocery outlets included in the analysis.

TABLE 4 **Store characteristics of the stores used in the analysis**

	<i>Net sales area sq m</i>	<i>Price measure £</i>	<i>Other attributes (share of stores having these attributes)</i>	
Min	241	2.26	Petrol	31.6%
25%	818	2.36	ATM	70.4%
50%	1,640	2.62	Coffee shop/rest	40.0%
75%	3,326	3.17	Toilets	58.3%
Max	9,566	4.39		

Source: Data collected from main parties to the inquiry.

21. Store net sales area ranges from 241 to 9,566 sq metres. The median price measure amounts to £2.62. The large majority of stores have an ATM and nearly 60 per cent have toilets. 40 per cent of stores include a coffee shop or restaurant and around 30 per cent have a petrol forecourt.

Estimation results

22. This section presents the estimation results of the choice probability models. The first part reports the MMNL estimates based on major and minor shopping trips. The estimates are compared with those from a simple MNL model. In a discrete choice model the coefficient estimates represent the impact of a certain variable on consumer's utility. To assess the impact on market outcome we therefore compute the extent of consumer switching following a small but significant price increase and present these derived results in the second part.

Coefficient estimates

23. Tables 5 and 6 display the coefficient estimates of the MMNL model together with standard errors and the value of the log-likelihood function for major and minor shopping trips, respectively. For comparison, the tables also report the results of a corresponding MNL model. Most of the coefficient estimates of the MMNL models, and all of those of the MNL models, are statistically significant. While most of the coefficient estimates can be easily compared between the two models, those relating

to distance and price in the MMNL model have to be first converted to their expected utility impact. For example, for a household with characteristics z_i , the change in expected utility from a change in price is given by: $\partial E[u_{ij}] / \partial p_j = -e^{-(z_i' \beta_z + \sigma_p / 2)}$. The tables also present the utility impact which corresponds to the price and distance related coefficient estimates for a household with median characteristics, that is, of size 2 with 1 car and of social group C.

TABLE 5 Parameter estimates for the MNL and MMNL model, major trips

Variable	Coef	MMNL		MNL	
		Std err	Coef	Std err	
Net sales area (in '000 sq m)	0.17	0.01	0.12	0.01	
Presence of:					
Petrol forecourt	0.17	0.03	0.20	0.03	
ATM	0.27	0.06	0.25	0.05	
Restaurant/Coffee shop	0.16	0.04	0.18	0.03	
Toilet	0.47	0.06	0.57	0.05	
Fascia dummies:					
Asda	-7.21	1.35	-5.41	1.12	
Morrisons	-6.82	1.23	-5.22	1.03	
Sainsbury's	-5.05	0.93	-3.94	0.78	
Tesco	-6.58	1.24	-4.94	1.03	
Waitrose	-1.04	0.25	-0.84	0.21	
		<i>Utility impact</i>			
		<i>(for hh-size=2,</i>			
		<i>sgde=0)</i>			
<i>Price coefficients</i>					
Price (intercept in MMNL)	1.88	-7.43	0.18	-5.97	
Price hh-size interaction	0.06		0.01		
Price sgde interaction	-0.01		0.02		
Price sigma	0.00		0.01		
		<i>Utility impact</i>			
		<i>(for hh-size=2,</i>			
		<i>sgde=0,</i>			
		<i>car=1)</i>			
<i>Distance coefficients</i>					
Distance (intercept in MMNL)	-1.32	-0.18	0.13	-0.23	
Distance hh-size interaction	-0.01		0.01		
Distance sgde interaction	0.00		0.02		
Distance car interaction	-0.35		0.03		
Distance sigma	0.00		0.01		
Distance-price covariance	0.12		0.07		
log-lik.	-19,139.3			-22,967.4	
likelihood ratio index	0.59			0.34	

Source: CC analysis.

TABLE 6 Parameter estimates for the MNL and MMNL model, minor trips

Variable	Coef	MMNL		MNL	
		Coef	Std err	Coef	Std err
Net sales area (in '000 sq m)	0.09		0.01	0.06	0.01
Presence of					
Petrol forecourt	0.07		0.04	0.09	0.04
ATM	0.09		0.06	0.10	0.05
Restaurant/Coffee shop	0.07		0.05	0.08	0.04
Toilet	0.05		0.06	0.14	0.05
Fascia dummies					
Asda	-4.15		0.98	-3.47	0.84
Morrisons	-3.91		0.90	-3.20	0.77
Sainsbury's	-2.94		0.68	-2.53	0.58
Tesco	-3.96		0.90	-3.33	0.77
Waitrose	-0.52		0.19	-0.45	0.17
		<i>Utility impact</i>			
		<i>(for hh-size=2,</i>			
		<i>sgde=0)</i>			
<i>Price coefficients</i>					
Price (intercept in MMNL)	1.41		0.20	-3.87	0.72
Price hh-size interaction	0.04		0.01		
Price sgde interaction	-0.01		0.02		
Price sigma	0.00		0.01		
		<i>Utility impact</i>			
		<i>(for hh-size=2,</i>			
		<i>sgde=0,</i>			
		<i>car=1)</i>			
<i>Distance coefficients</i>					
Distance (intercept in MMNL)	-2.02		0.22	-0.26	0.00
Distance hh-size interaction	-0.03		0.01		
Distance sgde interaction	-0.00		0.03		
Distance car interaction	-0.22		0.03		
Distance sigma	0.00		0.01		
Distance-price covariance	0.64		0.10		
log-lik.	-12,366.3			-14,160.1	
likelihood ratio index	0.49			0.36	

Source: CC analysis.

24. The MNL estimation results exhibit only smaller differences compared with the MMNL estimates. While the effect of the net sales area and other store characteristics is comparable and positive in both models for both major and minor trips, the fascia coefficients vary slightly more between MMNL and MNL for major trips. However, the ordering is maintained, that is, all fascias still have a lower stand-alone utility value compared with Somerfield, which is excluded. Everything else being constant, Asda provides the lowest value, followed by Morrisons and Tesco.

25. Price sensitivity is slightly higher in the MMNL models for all types of households. The sensitivity to drive-time is estimated to be higher for only some households undertaking major shopping trips but is otherwise always estimated to be lower in the MMNL models. For example, in the MNL model having to drive 1 additional minute

reduces expected utility for major trips by 0.23, while the decline for the median household, that is a household with two members and one car that belongs to social group C, is 0.18 in the MMNL model. For a similar household type, the corresponding estimate for price is 5.97 for the MNL model and 7.43 for the MMNL model. In the MMNL model, the negative impact of spending additional time driving is weaker for larger households and households with a car, while the effect of the social grade is not statistically significant. The impact of the social grade on the price sensitivity is equally not significant. In contrast, larger households tend to be more price sensitive. By construction, in the MNL the household type does not affect its price or distance sensitivity.

26. The low standard deviations of the random price and distance coefficient estimates suggest that consumer heterogeneity with respect to change in price and drive-time is accounted for by the socio-demographic variables included in the model. However, the estimates of the standard deviations of the mixing distribution are not significant. Furthermore, conditional on their socio-demographic characteristics, more price-sensitive consumers are also more sensitive to distance. This effect is statistically significant.
27. Comparing major and minor trips, we see that for major trips the size of the store and the other store characteristics matter more. Conditional on household characteristics, price sensitivity is higher for major trips and so is sensitivity to distance. On the other hand, the price–distance covariance is much higher for minor trips. Together with the slightly higher variance estimates, this implies that our socio-demographic variables do not represent differences in choice of grocery store for minor trips as well as they do for major trips.

28. The MNL model, if appropriate, can be estimated more efficiently than the MMNL model because in this case it would impose valid restrictions and it does not require simulation. Hence, it is of interest to examine empirically whether the restriction imposed by the MNL model, which is nested within the class of MMNL models, holds in this sample. The null hypothesis of the MNL being appropriate can be tested by means of a Lagrange multiplier (LM) test. This test has the appealing property that its asymptotic χ^2 distribution does not depend on the mixing distribution. Details of the test procedure are given in McFadden and Train (2000). For the models considered in Table 2, the LM test statistic takes the value 900.27, which exceeds the 1 per cent critical value of a χ^2 which is 9.21. Hence, the null hypothesis of no mixing (ie MNL) can be robustly rejected. In the analysis that follows we will concentrate on the results from the MMNL model.
29. In addition, the log-likelihood value is higher for the MMNL model than for the MNL model with both samples. While informative, these values are not directly comparable across the two models. Conditional on the data, the log-likelihood value is a constant in the MNL model while it is a random variable in the MMNL model, due to the additional simulation noise. In other words, repeated simulation samples, conditional on the $\{z_j, j = 1, \dots, n\}$, will generate a distribution of the value of the simulated log-likelihood function whose variance is due to simulation noise. The simulation estimator is computed based on ten random draws for each household. It may also be worth noting that the likelihood ratio index for the estimated MMNL model of 0.59 compares favourably to the likelihood ratio index for the estimated MNL model, which is 0.34. However, the same qualification applies with regard to comparability for the values of the log-likelihood functions evaluated at the estimators.

The model's predictions

30. Table 7 presents a comparison between the actual market shares of the different fascia in the sample with those predicted by the MMNL model.

TABLE 7 Comparison of actual and predicted market shares of fascias in the sample, MMNL model

Fascia	Market shares			
	Major trips		Minor trips	
	Actual	Predicted	Actual	Predicted
Asda	23.85	23.84	19.71	19.69
Morrisons	15.72	15.71	16.48	16.45
Sainsbury's	17.38	17.40	18.82	18.85
Somerfield	4.25	4.26	10.96	10.98
Tesco	36.91	36.90	30.22	30.19
Waitrose	1.89	1.89	3.81	3.84
Total	100.00	100.00	100.00	100.00

Source: Sample from the TNS Consumer Panel and CC analysis.

31. As Table 8 shows, the model also predicts the share of consumers which shop at stores of different sizes. More than 90 per cent of consumers go to stores above 1,400 sq metres for their major shopping trips, and just above 80 per cent for minor shopping trips. In general, the model slightly under-predicts the share of consumers going to large stores.

TABLE 8 Actual and predicted share of consumers shopping at different size stores

	Market shares			
	Major trips		Minor trips	
	Actual	Predicted	Actual	Predicted
Over 1,400 sq m store	92.27	90.52	82.52	81.35
Over 2,000 sq m store	82.95	80.61	70.42	69.10
Smaller than 1,000 sq m store	3.41	4.81	9.19	10.51

Source: Sample from the TNS Consumer Panel and CC analysis.

32. The model also replicates the share of consumers shopping within different drive-time bands from their home. The model's predictions, presented in Table 9, are very close to the actual sample distribution as the model predicts that most consumers shop within 15 minutes from their home. Only a few households travel more than

20 minutes for their grocery shopping. For minor trips, consumers on average shop closer to home.

TABLE 9 Comparison of actual and predicted shares of consumers' shopping behaviour in terms of drive-time distance to their home

per cent

<i>Fascia</i>	<i>Major trips</i>		<i>Minor trips</i>	
	<i>Actual</i>	<i>Predicted</i>	<i>Actual</i>	<i>Predicted</i>
<=5 mins	29.85	28.27	39.22	35.95
5 to 10 minutes	35.57	34.08	33.20	34.38
10 to 15 minutes	18.82	21.32	15.27	18.14
15 to 20 minutes	9.66	11.80	7.75	8.79
Beyond 20 minutes	6.11	4.54	4.56	2.74

Source: Sample from the TNS Consumer Panel and CC analysis.

33. We conclude from these results that the model adequately predicts consumers' choice of grocery store as given in the two samples.

Predicted reaction to a change in price

34. In this section we use the model to analyse the reaction of consumers to a change in price. The logit model allows us to compute the probability of shopping at each store in the household's choice set. For the following derived results, we compute the probability of shopping at a certain subgroup of stores (for example, all Asda stores) before and after a price increase. The results in the following tables report either the average difference in these probabilities across all consumers (equivalent to change in percentage point market share of this group) or the relative difference (proportion or fraction of original market share).
35. The resulting estimates permit us to assess the competitive constraints that different groups exert on each other. To assess whether a group with certain characteristics will exert a stronger competitive pressure than others we need to use the MMNL estimates as these do not rely on the IIA assumption. For this purpose, we compute for each group changes in the predicted share of shopping trips based on a 2 and a 5 per cent price increase as outlined below.

change in own share. :

$$E \left[\frac{P_{ij}(x, p, dist_i, z_i; \theta_x, \beta) - P_{ij}(x, p_j(1 + \alpha), p_k, dist_i, z_i; \theta_x, \beta)}{P_{ij}(x, p, dist_i, z_i; \theta_x, \beta)} \right]$$

change in rival share. :

$$E \left[\frac{P_{ij}(x, p, dist_i, z_i; \theta_x, \beta) - P_{ij}(x, p_j, p_k(1 + \alpha), dist_i, z_i; \theta_x, \beta)}{P_{ij}(x, p, dist_i, z_i; \theta_x, \beta)} \right]$$

j here indexes one subgroup, eg all Asda stores, whereas k indexes the group of remaining stores.⁴ p_j denotes all prices of stores that belong to subgroup j and p_k the prices of the remaining stores. The price increase is measured by α . The expectation is based over all consumers included in the sample.

36. The results for different fascias are displayed in Table 10. This table can be read as follows. Focusing on the first row, if Asda increases its price by 2 per cent, it is predicted to lose 18.36 per cent of households. As a result, Morrisons will increase its market share by 6.69 per cent, Sainsbury's, Tesco and Somerfield by between 5 and 6 per cent and Waitrose by 3.24 per cent. We see that the differences between these changes are small; while, for example, Morrisons is the primary beneficiary of an Asda price increase, the relative gains of Sainsbury's, Tesco and Somerfield are only slightly lower.
37. Generally, there is no marked distinction between the different rivals. That is, every fascia seems to gain from a rival price increase. The MMNL estimates generally suggest that the fascia that are included in our sample are relatively close competitors to each other. However, we note a few exceptions. Waitrose does not benefit as much from an Asda or a Morrisons price increase and Asda and Morrisons do not gain as much following a Waitrose price increase.

⁴In order to reduce notational burden, we use the same indexing here as before. While before j referred to a specific store, now it indexes a subgroup of stores.

TABLE 10 Change in share of major shopping trips for a 2 and 5 per cent price Increase

	<i>per cent</i>					
	<i>Asda</i>	<i>Morrisons</i>	<i>Sainsbury's</i>	<i>Somerfield</i>	<i>Tesco</i>	<i>Waitrose</i>
<i>2% price increase</i>						
<i>Asda</i>	-18.36	6.69	5.83	5.08	5.52	3.24
<i>Morrisons</i>	4.41	-20.82	3.66	4.28	3.65	2.84
<i>Sainsbury's</i>	4.65	4.41	-24.05	5.57	5.40	8.17
<i>Somerfield</i>	1.18	1.48	1.57	-31.06	1.35	1.89
<i>Tesco</i>	8.98	8.99	11.00	9.39	-16.52	11.99
<i>Waitrose</i>	0.33	0.43	0.98	0.84	0.72	-32.61
<i>5% price increase</i>						
<i>Asda</i>	-41.91	15.42	13.33	11.75	12.50	7.27
<i>Morrisons</i>	9.56	-45.58	8.03	9.98	7.97	6.29
<i>Sainsbury's</i>	9.78	9.37	-51.48	12.48	11.58	18.42
<i>Somerfield</i>	2.26	2.90	3.01	-60.12	2.63	3.68
<i>Tesco</i>	20.59	20.96	25.95	22.53	-38.54	28.94
<i>Waitrose</i>	0.63	0.85	1.91	1.76	1.40	-63.89

Source: CC analysis.

38. Table 11 presents the results for minor trips. The pattern of results is not markedly different from that of Table 10.

TABLE 11 Change in share of minor trips for a 2 and 5 per cent price increase

	<i>per cent</i>					
	<i>Asda</i>	<i>Morrisons</i>	<i>Sainsbury's</i>	<i>Somerfield</i>	<i>Tesco</i>	<i>Waitrose</i>
<i>2% price increase</i>						
<i>Asda</i>	-11.41	3.23	2.85	2.69	2.70	1.73
<i>Morrisons</i>	2.78	-12.18	2.27	2.42	2.32	1.62
<i>Sainsbury's</i>	3.11	2.85	-14.27	3.40	3.45	5.03
<i>Somerfield</i>	2.15	2.24	2.47	-18.33	2.25	2.01
<i>Tesco</i>	4.33	4.30	5.08	4.52	-10.66	5.31
<i>Waitrose</i>	0.46	0.50	1.20	0.67	0.87	-19.16
<i>5% price increase</i>						
<i>Asda</i>	-26.98	7.66	6.74	6.38	6.38	4.03
<i>Morrisons</i>	6.49	-28.48	5.29	5.73	5.42	3.77
<i>Sainsbury's</i>	7.09	6.55	-32.95	7.95	7.98	11.87
<i>Somerfield</i>	4.68	4.93	5.37	-40.14	4.95	4.41
<i>Tesco</i>	10.24	10.26	12.14	10.89	-25.43	12.77
<i>Waitrose</i>	0.99	1.09	2.63	1.49	1.93	-42.16

Source: CC analysis.

39. Tables 12 and 13 present similar results but break down household switching by store sizes for major trips. Generally, the results show that the vast majority of switching following a price increase by one fascia benefits large stores. For example, if Asda increases its price by 2 per cent, it loses 4.38 percentage points of its market share: 3.45 percentage points or 80.82 per cent are lost to competitors with net sales

area above 2,000 sq metres and 3.94 percentage points or 89.95 per cent to competitors with net sales area above 1,400 sq metres. Fascias with predominately smaller stores, such as Waitrose, lose comparably less to large competitors (here 77.42 per cent to stores above 2,000 sq metres following a 2 per cent price increase). If only large stores of a fascia increase their price, the picture is similar for stores that mostly have either large or small stores. In contrast, Tesco, which has both, shows slightly different effects: 81.64 per cent of households are lost to large competitor stores after a 2 per cent price increase of all Tesco stores, and 75.6 per cent of consumers are lost to large competitors after a 2 per cent price increase of only large Tesco stores.

TABLE 12 **Change in predicted choice probabilities by store size, large stores: \geq 2,000 sq metres net sales area, major trips**

Fascia	Percentage point change in predicted choice probabilities						
	In reaction to price increase of stores of all sizes of fascia				In reaction to price increase of large stores of fascia		
	For fascia	For large same fascia	For large competitor fascia	Diversion ratio	For large same fascia	For large competitor fascia	Diversion ratio
<i>2% price increase</i>							
Asda	-4.38	-4.32	3.54	-80.82	-4.33	3.49	-80.60
Morrisons	-3.27	-2.72	2.63	-80.43	-2.75	2.24	-81.45
Sainsbury's	-4.19	-3.62	3.30	-78.76	-3.73	2.88	-77.21
Somerfield	-1.32	-0.03	1.05	N/A	-0.03	0.03	N/A
Tesco	-6.10	-4.83	4.98	-81.64	-5.22	3.95	-75.67
Waitrose	-0.62	-0.20	0.48	-77.42	-0.20	0.16	-80.00
<i>5% price increase</i>							
Asda	-9.99	-9.87	8.08	-80.88	-9.88	7.98	-80.77
Morrisons	-7.16	-5.94	5.73	-80.03	-5.99	4.86	-81.14
Sainsbury's	-8.96	-7.73	7.02	-78.35	-7.89	6.05	-76.68
Somerfield	-2.56	-0.06	2.02	N/A	-0.06	0.05	N/A
Tesco	-14.22	-11.26	11.56	-81.29	-11.93	9.01	-75.52
Waitrose	-1.21	-0.38	0.93	-76.86	-0.39	0.30	-76.92

Source: CC analysis.

Notes:

1. We omit the results for Somerfield, as there are very few Somerfield stores of more than 1,400 sq metres in our sample and thus the resulting estimates are likely not very accurate. Equally, the results for Waitrose should be interpreted with caution.
2. N/A = not available.

TABLE 13 **Change in predicted choice probabilities by fascia and size groups, large stores: >= 1,400 sq metres net sales area, major trips**

Fascia	Percentage point change in predicted choice probabilities						
	In reaction to price increase of stores of all sizes of fascia				In reaction to price increase of large stores of fascia		
	For fascia	For large same fascia	For large competitor fascia	Diversion ratio	For large same fascia	For large competitor fascia	Diversion ratio
<i>2% price increase</i>							
Asda	-4.38	-4.38	3.94	-89.95	-4.38	3.94	-89.95
Morrisons	-3.27	-3.22	2.89	-88.38	-3.23	2.84	-87.93
Sainsbury's	-4.19	-3.96	3.72	-88.78	-4.01	3.51	-87.53
Somerfield	-1.32	-0.22	1.23	N/A	-0.23	0.20	N/A
Tesco	-6.10	-5.44	5.56	-91.15	-5.70	4.93	-86.49
Waitrose	-0.62	-0.44	0.54	-87.10	-0.45	0.38	-84.44
<i>5% price increase</i>							
Asda	-9.99	-9.99	9.00	-90.09	-9.99	8.99	-89.99
Morrisons	-7.16	-7.05	6.29	-87.85	-7.07	6.19	-87.55
Sainsbury's	-8.96	-8.46	7.93	-88.50	-8.54	7.45	-87.24
Somerfield	-2.56	-0.43	2.37	N/A	-0.44	0.39	N/A
Tesco	-14.22	-12.71	12.94	-91.00	-13.16	11.37	-86.40
Waitrose	-1.21	-0.88	1.05	-86.78	-0.88	0.75	-85.23

Source: CC analysis.

Notes:

1. We omit the results for Somerfield, as there are very few Somerfield stores of more than 1,400 sq metres in our sample and thus the resulting estimates are likely not very accurate. Equally, the results for Waitrose should be interpreted with caution.
2. N/A = not available.

40. The corresponding results for minor trips are presented in Tables 14 and 15. Besides the lower overall amount of consumer switching, which is a general result for minor trips resulting from the lower price sensitivity, fewer of those who switch do so to large competitors.

TABLE 14 **Change in predicted choice probabilities by store size, large stores: >= 2,000 sq metres net sales area, minor trips**

per cent

Percentage point change in predicted choice probabilities

Fascia	In reaction to price increase of stores of all sizes of fascia				In reaction to price increase of large stores of fascia		
	For fascia	For large same fascia	For large competitor fascia	Diversion ratio	For large same fascia	For large competitor fascia	Diversion ratio
<i>2% price increase</i>							
Asda	-2.25	-2.20	1.55	-68.89	-2.21	1.52	-68.78
Morrisons	-2.00	-1.61	1.40	-70.00	-1.63	1.16	-71.17
Sainsbury's	-2.69	-2.15	1.77	-65.80	-2.25	1.45	-64.44
Somerfield	-2.01	-0.04	1.53	NA	-0.05	0.04	NA
Tesco	-3.22	-2.30	2.20	-68.32	-2.50	1.60	-64.00
Waitrose	-0.73	-0.17	0.50	-68.49	-0.17	0.12	-70.59
<i>5% price increase</i>							
Asda	-5.31	-5.21	3.68	-69.30	-5.22	3.60	-68.97
Morrisons	-4.68	-3.75	3.26	-69.66	-3.80	2.71	-71.32
Sainsbury's	-6.21	-4.95	4.07	-65.54	-5.14	3.29	-64.01
Somerfield	-4.41	-0.09	3.34	NA	-0.10	0.07	NA
Tesco	-7.68	-5.48	5.24	-68.23	-5.88	3.77	-64.12
Waitrose	-1.62	-0.37	1.10	-67.90	-0.38	0.26	-68.42

Source: CC analysis.

Notes:

1. We omit the results for Somerfield, as there are very few Somerfield stores of more than 1,400 sq metres in our sample and thus the resulting estimates are likely not very accurate. Equally, the results for Waitrose should be interpreted with caution.
2. N/A = not available.

TABLE 15 **Change in predicted choice probabilities by fascia and size groups, large stores: >= 1,400 sq metres net sales area, minor trips**

per cent

Percentage point change in predicted choice probabilities

Fascia	In reaction to price increase of stores of all sizes of fascia				In reaction to price increase of large stores of fascia		
	For fascia	For large same fascia	For large competitor fascia	Diversion ratio	For large same fascia	For large competitor fascia	Diversion ratio
<i>2% price increase</i>							
Asda	-2.25	-2.24	1.80	-80.00	-2.24	1.80	-80.36
Morrisons	-2.00	-1.96	1.59	-79.50	-1.97	1.55	-78.68
Sainsbury's	-2.69	-2.44	2.11	-78.44	-2.50	1.91	-76.40
Somerfield	-2.01	-0.29	1.81	N/A	-0.31	0.25	N/A
Tesco	-3.22	-2.68	2.60	-80.75	-2.83	2.17	-76.68
Waitrose	-0.73	-0.44	0.60	-82.19	-0.45	0.35	-77.78
<i>5% price increase</i>							
Asda	-5.31	-5.30	4.26	-80.23	-5.30	4.25	-80.19
Morrisons	-4.68	-4.58	3.71	-79.27	-4.60	3.63	-78.91
Sainsbury's	-6.21	-5.63	4.86	-78.26	-5.74	4.39	-76.48
Somerfield	-4.41	-0.62	3.95	N/A	-0.66	0.54	N/A
Tesco	-7.68	-6.40	6.20	-80.73	-6.70	5.12	-76.42
Waitrose	-1.62	-0.98	1.31	-80.86	-0.99	0.77	-77.78

Source: CC analysis.

Notes:

1. We omit the results for Somerfield, as there are very few Somerfield stores of more than 1,400 sq metres in our sample and thus the resulting estimates are likely not very accurate. Equally, the results for Waitrose should be interpreted with caution.
2. N/A = not available.

41. Up to this point we have focused on the substitution patterns of households with respect to fascia and store size. Table 16 focuses on household substitution with respect to drive-time. These results give some explanation to the geographic dimension of competition. This table shows which fascia households switch to for their major trip if their nearby stores increase prices. If, for example, all stores within 10 minutes of a consumer increase their price by 2 per cent, this group loses 5.85 percentage points of market share. Of these households, 60.2 per cent (or 3.52 percentage points) are lost to stores within 10 to 15 minutes and only 7.5 per cent (0.44 percentage points) are lost to stores beyond 20 minutes' drive-time. In general, this analysis shows that following a price increase of their nearby stores, those households who switch predominantly switch to the next closest store group.

TABLE 16 **Change in predicted choice probabilities by distance bands following a price increase of stores in different distances from the consumer, major trips**

	<i>per cent</i>				
	<i>Probability of shopping at store in distance band (excludes lower and includes upper bound)</i>				
	<i><=5 mins</i>	<i>5–10 min</i>	<i>10–15 min</i>	<i>15–20 min</i>	<i>>20 min</i>
Actual shares	29.85	35.57	18.82	9.66	6.11
<i>Predicted choice probabilities</i>					
Before price increase	28.27	34.08	21.32	11.80	4.54
After 2% price increase of stores in distance					
<=5 min	24.44	35.94	22.47	12.43	4.72
Difference to before	-3.83	1.86	1.15	0.63	0.18
Sum of switching	-3.83	3.82			
<=10 min	26.11	30.39	24.84	13.67	4.98
Difference to before	-2.16	-3.69	3.52	1.87	0.44
Sum of switching		-5.85	5.83		
<=15 min	27.25	32.55	19.91	14.97	5.32
Difference to before	-1.02%	-1.53%	-1.41%	3.17%	0.78%
Sum of switching			-3.96%	3.95%	
After 5% price increase of stores in distance					
<=5 min	19.10	38.48	24.07	13.33	5.02
Difference to before	-9.17	4.40	2.75	1.53	0.48
Sum of switching	-9.17	9.16			
<=10 min	22.55	24.65	30.35	16.70	5.75
Difference to before	-5.72	-9.43	9.03	4.90	1.21
Sum of switching		-15.15	15.14		
<=15 min	25.34	29.59	17.42	20.91	6.73
Difference to before	-2.93	-4.49	-3.90	9.11	2.19
Sum of switching			-11.32	11.30	

Source: CC analysis.

42. For minor shopping trips, closeness to the consumer is even more important. Table 17 shows that on average only 3.33 percentage points of households are lost when the stores within 10 minutes of a consumer increase their price by 2 per cent and 65.2 per cent (or 2.17 percentage points) are lost to stores within 10 to 15 minutes' drive-time. Only 5.4 per cent (or 0.18 percentage points) are lost to stores beyond 20 minutes.

TABLE 17 **Change in predicted choice probabilities by distance bands following a price increase of stores in different distances from the consumer, minor trips**

	<i>per cent</i>				
	<i>Probability of shopping at store in distance band (excludes lower and includes upper bound)</i>				
	<i><=5 mins</i>	<i>5-10 min</i>	<i>10-15 min</i>	<i>15-20 min</i>	<i>>20 min</i>
Actual shares	39.22	33.20	15.27	7.75	4.56
Predicted choice probabilities					
Before price increase	35.95	34.38	18.14	8.79	2.74
After 2% price increase of stores in distance					
<=5 min	33.15	35.91	18.96	9.16	2.81
Difference to before	-2.80	1.53	0.82	0.37	0.07
Sum of switching	-2.80	2.79			
<=10 min	34.55	32.45	20.31	9.77	2.92
Difference to before	-1.40	-1.93	2.17	0.98	0.18
Sum of switching		-3.33	3.33		
<=15 min	35.35	33.73	17.60	10.28	3.04
Difference to before	-0.60%	-0.65%	-0.54%	1.49%	0.30%
Sum of switching			-1.79%	1.79%	
After 5% price increase of stores in distance					
<=5 min	29.03	38.13	20.18	9.73	2.94
Difference to before	-6.92	3.75	2.04	0.94	0.20
Sum of switching	-6.92	6.93			
<=10 min	32.23	29.37	23.82	11.36	3.22
Difference to before	-3.72	-5.01	5.68	2.57	0.48
Sum of switching		-8.73	8.73		
<=15 min	34.30	32.52	16.65	12.94	3.58
Difference to before	-1.65	-1.86	-1.49	4.15	0.84
Sum of switching			-5.00	4.99	

Source: CC analysis.

43. Finally, we compute the relative change in predicted choice probabilities following a price increase of nearby stores. This provides some insight into the relative importance of drive-time. When stores within 5 minutes increase their price by 2 per cent, they are predicted to lose 13.55 per cent of their market share for major trips. This share decreases quickly if we increase the distance to stores within 10, 15 and 20 minutes from a consumer's home. When comparing these results with the results

which we obtained before on the fascias, we see that while each fascia loses between 18 and 32 per cent of their market share following a 2 per cent fascia price increase, the group of nearby stores loses only between 1.23 and 13.55 per cent. On this basis, it seems that households care more about the distance to the store than about the fascia.

TABLE 18 **Relative change in market share** *per cent*

	<i>Relative change in market share following</i>			
	<i>Major trips</i>		<i>Minor trips</i>	
	<i>2% price increase</i>	<i>5% price increase</i>	<i>2% price increase</i>	<i>5% price increase</i>
Stores within 5 minutes	-13.55	-32.44	-7.79	-19.25
Stores within 10 minutes	-9.38	-24.30	-4.73	-12.41
Stores within 15 minutes	-4.73	-13.53	-2.02	-5.65
Stores within 20 minutes	-1.23	-3.58	-0.46	-1.27

Source: CC analysis.

Construction of the price measure

1. The price measure is based on the responses to question 58 of the main party questionnaire, in which the CC defined around 220 product categories and asked parties to provide store-level prices for their top-selling product (SKU) in the particular category (top-selling across all stores of the retailer—for example, for Tesco’s top-selling SKUs across all Tesco fascias including One-Stop).
2. For many product categories, the information submitted by different grocery retailers is for different products. For example, the ice-cream SKU for one retailer provided the price of Häagen-Daz and another retailer submitted the price of its own-label product.

Selection of component goods

3. In selecting component products for our price measure we had to make a trade-off between increasing store coverage of the respective price measure and decreasing the number of products in the basket. We finally selected 37 out of the 220 products for which we had the price. These were for the products we had received information on, for nearly identical products, and where information was provided by almost all stores.
4. We ended up with a small number of branded products for which (almost) all retailers provided prices for exactly the same product—for example, for lemonade, the price of Schweppes Original Lemonade.
5. We added to these a larger number of product definitions that did not include well-known brands (KVIs)—these product definitions mainly include basic groceries like flour, fruits, vegetables and meat.

Aggregation of the individual prices

6. For our price measure we compute a revenue-weighted average price over the 37 products which we selected. As weights for the individual prices we use the national revenue share of this product in total national revenues for all component products.

7. We first calculate the total revenue generated by sales of the component goods across all stores (national GBP sales of the component goods). Each price weight in the basket is then the product's share of total basket revenues (national GBP sales of this product divided by national GBP sales of all products in the basket). Thus the price of bananas, for example, tends to have a larger weighting in the price measure, while the price of cabbage, for example, tends to have a small weighting.