Embedding Consumer Taste for Location into a Structural Model of Equilibrium

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Abstract

Given that brands (products) are location specific in terms of coverage of retail stores, we allow consumers to have preferences over location and products to carry distribution costs, alongside preferences and costs over other observable and unobservable product characteristics. We embed these considerations into Berry, Levinsohn and Pakes (1995) to jointly estimate demand and cost parameters for brands (products) in Retail Carbonated Soft Drinks. Allowing for location has a very significant impact on estimated primitives and the predictive power of the structural model. As a counterfactual exercise we show the effects on welfare of an equilibrium that results from a change in the distribution of consumer taste for location.

KEYWORDS:Consumer taste for location distributions, differentiated products, discrete choice, aggregation, structural model and retail carbonated soft drinks.

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1 Introduction

Embedding heterogenous transportation costs into the utility of consumers has a long theoretical history. Familiar theoretical settings include the linear city of Hotelling (1929) and D'Aspremont et al (1979) and circular city of Salop (1979)[1]. A core innovation of this paper is to embed consumer preferences for location, drawn from product specific retail locations, into demand and, via a structural model of equilibrium, we model products to carry distribution costs. We embed these considerations, together with preferences and costs associated with other observable and unobservable product characteristics, into the estimation routine of Berry, Levinsohn and Pakes, BLP, (1995) to jointly estimate the primitives of demand and cost for 178 brands (products) in Retail Carbonated Soft Drinks over 28 bi-monthly periods. Allowing for product retail locations greatly enriches the demand and cost primitives that can be used in structural models of retail industries[2].

We simulate the distribution of consumer tastes for product location using AC Nielsen data on store coverage of brands (products) in retail Carbonated Soft Drinks (CSD). The nature of aggregation over stores is measured as a weighted (effective) coverage of stores, where the weight given to each store is its size (market share) in terms of the overall market level CSD turnover. Brands belonging to the same company, or segments of defined product characteristics, have very heterogenous effective coverage of the 12,000 outlets. We exploit this product *(j)* heterogeneity by randomizing over effective store coverage to create a distribution of consumers with and without disutility resulting from each brand's location. Since stores, weighted by size, locate in a catchment area, not covering a store clearly creates distance to a brand for consumers in this catchment area. We simulate a probability distribution of consumers likely to find the brand in their nearest shop and others that will not and incur disutility [3].

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[1]The characterization of an equilibrium in oligopoly in the presence of heterogenous consumer transportation costs still generates theoretical interest [see Irmen and Thisse (1998)].

[2]In this paper we use the estimated primitives to undertake a static analysis of the retail Carbonated Soft Drinks (CSD) market. See Bajari, Benkard and Levin (2004) for their use in dynamic models of industries.

[3]Clearly an individual chooses the product that gives the highest utility. For an individual some products may have a disutility associated with not being in the nearest shop, others do not. One could try to back out the nature of transportation costs for individuals, based on simulations of the number of stores to be searched before finding the product. We experimeted with this idea. The additionally draws would be undertaken using more structure (defining

A major innovation of the BLP framework is that it allows one to estimate a random utility model at the product level interacting exogeneous distributions in consumer characteristics (income levels) with product level characteristics (particularly price) to impose a more general functional form for utility and allow for substitution patterns that are more plausible[4]. This requires an estimation strategy that involves simulation and numerical methods in moving from the individual to aggregate demands (see Mc Fadden (1989), Pakes and Pollard (1989) for further details). Unfortunately, a reliance on the market-level *(t)* distributions of consumer characteristics, do not give the degrees of freedom one might like[5]. In this paper we improve our estimates of demand primitives allowing for a distribution of consumer taste for product specific location and it's interaction with price. Allowing for product *(j)* specific consumer heterogeneity has a significant impact on estimated primitives and on the predictive power of the structural model. Marketing data from retail stores is an obvious source of information on product characteristics suitable for the BLP estimation routine. In this paper we highlight important efficiency gains from using information on distribution structures, also available from marketing companies, in the BLP estimation routine.

The BLP estimation routine, based on Berry (1994), also allows for correlations between product prices and unobservable (to the econometrician) product characteristics. We model consumer choice and pricing (short-run quantity and price movements) taking the strategic placing of brands over stores as given, among other longer term choices in product characteristics. Given that a brands' effective coverage of stores by companies varies greatly across products, we allow the distribution of consumer taste for product specific location and its interaction with price to be correlated with the unobservable in demand. In addition, we allow distribution costs associated with product specific location to be cor-

the max number of stores searched) and did not lead to a significant change in our results. We prefer to work with the simple idea that individuals have some disutility or not. The level of disutility is the same irrespective of whether an individual travels to the second or tenth nearest store. This assumption works for Carbonated Soft Drinks, but may not be realistic for expensive items such as automobiles.

[4]The theoretical considerations and the algorithm necessary to estimate the random coefficient model, not jointly estimated with the cost function, is nicely outlined in Nevo (2000) and Nevo (2001).

[5]The distribution of consumer characteristics relevant to products inside the market may well be different to those purchasing the outside option (see Mariuzzo, 2004). Likewise the distribution of relevant consumer characteristics may also vary dramatically across products inside the market, see Berry Levinsohn and Pakes (2004) and Petrin (2002).

related with the unobservable in the cost function. Finally, we motivate the use of product level store coverage and inventory data to construct Hausman and Taylor (1981) and BLP (1995) type instrumental variables.

In a counterfactual exercise, holding the parameters of the surface of the utility and cost function constant, as well as the distribution of non-price product characteristics constant, we examine the effects on welfare in an equilibrium that results from a change in the distribution of consumer taste for product location. By holding marginal costs fixed we change the simulated numbers of consumers having no disutility due to having products in their nearest shop by expanding effective store coverage for each product by one per cent. Solving for a new short-run equilibrium in prices *and* market shares at the product level, resulting for an exogenous change in the distribution of consumer taste characteristics, is a non-trivial exercise in the presence of non-linear functional forms. We introduce a numerical method to solve for the new equilibrium as part of a nonlinear programming problem. Clearly, reducing the numbers of consumers with disutility for all products inside the market induces all own and cross-price elasticities to become more elastic. This has the effect of increasing price competition inside the market but it also induces a market expansion effect that brings consumers in from consuming the outside good. Overall, consumer and producer surplus increases as a result of a this change in the distribution of consumer characteristics[6].

The next section summarizes the Irish Retail Carbonated Soft Drink market and our data. In Section 3 we outline the underlying theoretical model. Section 4 highlights our estimation methods and computational techniques. In Section 5 we discuss our estimation results and undertake some positive analysis of the industry. In section 6 we undertake a counterfactual by changing the distribution of consumer taste for location. We outline our conclusion in section 7.

[6]Mariuzzo, Walsh and Whelan (2003), using the data in this paper, offer anti-trust authorities a simple nested logit regression to get a rough picture of the market share and power relationship in a differentiated product industry. If one wishes to go further and undertake counterfactuals on equilibrium price and quantity outcomes, one is forced to jointly estimate the parameters of the utility and cost function with as much flexibility in functional forms as possible. Flexibility implies one has to deal with nonlinearities using numerical methods in the estimation procedure and in the counterfactual exercise. In this paper, we make advances in the specification of functional forms and in the procedure for undertaking counterfactuals.

2 Industry and Data

AC Nielsen collated a panel database of all brands in Carbonated Soft Drinks distributed throughout 12,000 Irish retail stores for use in our empirical analysis[7]. The database provides 28 bi-monthly periods spanning October 1992 to March 1997 for 178 brands, identified for 13 firms and 40 product characteristics within the particular business of Retail Carbonated Soft Drinks. The data record the retail activities of both Irish and Foreign owned brands/firms selling throughout the stores of the Irish retail sector. Large stores are supermarket chains that cater for one-stop shopping. Small outlets are convenience stores that cater for impulse shopping. The structure of retail outlets that brands sold across was stable throughout the period we study.

The retail market for Carbonated Soft Drinks in Ireland is broadly similar in structure to the U.S. In 1997, the top two firms collectively account for 73 per cent of the Irish market and 75 per cent of the US retail market. Inequality in retail sales as measured by the Gini co-efficient is 0.72 in Ireland and 0.68 in the US. There are differences between Ireland and the US that are typical of European Carbonated Soft Drinks markets. These differences are highlighted in case studies of several countries in Sutton (1991). The Cola segment of the market is 35 to 40 per cent in Europe, compared to 63 per cent in the US. Flavor segments are similar to the US in Ireland. Chain store own-labels are a small feature of the Irish Market. Like the US the Irish market is heavily branded market.

We have brand level information on the per litre brand price (weighted average of individual brand unit prices across all stores selling the brand, weighted by brand sales share within the store), quantity (thousand liters), sales value (thousand Irish pounds), store coverage (based on counts of stores size weighted by store size in terms of overall Carbonated Soft Drink turnover), inventories (number of days to stock out on day of audit given the current rate of brand sales during the bi-monthly period), firm attachment and product (flavor, packaging, and diet) characteristics. An interesting feature of the AC Nielsen data is their identification of various product segments within the market for Carbonated Soft Drinks, which group clusters of brands by 40 characteristics: 4 flavors (Cola, Orange, Lemonade and Mixed Fruit), 5 different packaging types

[7] We are bound by a contract of confidentiality with AC Nielsen not to reveal information, not otherwise available on the market.

(Cans, Standard Bottle, 1.5 Litre, 2 Litre and Multi-Pack of Cans) and 2 different sweeteners, diet and regular. The number of the product characteristics was very stable throughout the period of this study[8]. To allow for flavor segments (Cola, Orange, Lemonade and Mixed Fruit) is standard in the analysis of Carbonated Soft Drinks [see Sutton (1991)].

To see why packaging format is recognized as a crucial feature of this market, in Figure I we graph the seasonal cycles of carbonated drink sales by packaging type. One must realize that 90 per cent of cans and standard bottles are impulse buys distributed through small stores. In contrast, the majority of 2 litre and multi-pack cans are distributed through one-stop supermarket shopping. The 1.5 litre is somewhere between these extremes. The industry has introduced different packaging to satisfy different consumer needs within both the impulse and one-stop shopping segments (Walsh and Whelan, 1999). For example, cans peak in the summer months of June and July, when people lunch outside in parks. In contrast, 2 Litre bottles sales peak over the winter months of December and January, the festive season. Packaging clearly represents different segments of the market. Thus, we have forty combinations of product characteristics delineated in our data. Packaging by time dummies turn out to be very important control variables in demand and cost. Not only do they control for different seasonal cycles in demand, but also for the nature of the buy (store) in terms of impulse (small store) or one-stop shopping (supermarket). In the cost function, packaging by time dummies control for plastic, glass and aluminium input costs that can change over-time. Packaging as a product characteristic tends to be omitted in studies of retail industries, such as Nevo (2000). Even though the focal point in this paper is to highlight the importance of product locations across stores, the importance of packaging in our functional forms and results is another contribution.

We define firm business as retail Carbonated Soft Drinks. Yet, firms may or may not place brands across the various segments, combinations of product characteristics, of the market. In Table 1 we document company coverage of segments and the within segments weighted coverage of stores, weighted by a stores share of the market level Carbonated Soft Drinks turnover. We undertake

[8]We take the emergence of such segments as an outcome of history. If in Carbonated Soft Drinks consumers were fully mobile across segments and advertising was very effective, the market would evolve to be dominated by one segment. Taste structures and advertising outlays, amongst other factors, have driven the current day segmentation of the market by product attribute , see Sutton (1998).

our analysis by comparing the top two companies, Coca-Cola Bottlers (Coca-Cola Co. franchise) and C&C (Pepsico franchise), with the group of smaller companies (mainly Irish/British owned). The top two companies have broad coverage of the product segments. We see that within segment store coverage is not company but brand specific. For example, Coca-Cola Bottlers has wide distribution with Regular Cola, by most packaging types, but market coverage is clearly less aggressive in regular Orange and Mixed Fruit characteristics. This is where competition from the small companies is greatest.

Details of the product characteristics and associated number of firms and brands they host are set out in Table 2. The structure of the market has large companies competing across most characteristics and facing competition from different small independents within each segment. In each segment market size to sunk cost and the nature of price and non-price competition seem to limit the number of firms that can operate (see Walsh and Whelan (2002a)). The number of firms that operate in each segment is quite small. Yet, due to certain local taste characteristics, particularly in orange and mixed fruit, and specialization into a subset of stores, small companies can fill a quality window and survive alongside the brands of large companies. Details of the product characteristics in terms of price per litre and unit sales and revenue shares are also outlined in Table 2.

In terms of market share and pricing, packaging matters. For example, 2 liters regular cola have lower prices and higher volume, while regular cola cans sell at higher prices with a lower volume. Yet, the revenue shares are not so different. How can we tell which products (segments and companies) earn more profit? We use a structural model to back-out estimates of mark-ups (marginal cost) for brands (segments and companies). Consumers are likely to have different tastes for packaging and brands incur different packaging costs, among other factors, which allow us to estimate primitives of demand and cost within a structural model and ascertain the role of packaging in the determination of mark-ups at the brand and segment level.

Another important aspect of the paper is to allow for brand specific locations to influence consumer taste and costs. We allow consumers to have preferences over location and products to carry distribution costs alongside preferences and costs associated with other product characteristics. In table 3 we detail effective store coverage and effective inventories levels, within the stores covered, by segments. Packaging type does indicate the nature of stores covered. The distribution structures in terms of unweighted store counts would reflect this. Cans and standard packaging are generally in many more stores that 2 litres. Yet, the trend in effective (market) coverage of stores is less obvious as the 2 litres will always cover the bigger stores. In addition, effective coverage by brands of the various segments does not change much overtime for regular brands. Diet brands tend to be a bit more volatile. The weighted average of inventories within the stores that a brand covers is measured as the number of days to stock out on the day of audit given the current rate of brand sales during the previous bi-monthly period. Net of the seasonal cycle how do brands, aggregated to segments, manage delivery costs? We see clearly that segments depending more on the impulse buys/small stores (indicated by the cans and standard packaging format), use inventories more. Delivery costs are clearly higher and can be reduced with the use of inventories. The use of inventories is pretty stable over time. We control for distribution costs coming from the degree of store coverage and, with inventories, the costs of distributing within the stores that are covered. In the following section we outline the demand side, the supply side and the market equilibrium.

3 The Model

We assume price taking individuals to be exogenously placed in different locations. Stores place themselves in consumer catchment areas. Stores may carry all products or only use a subset of the existing products. Our Carbonated Soft Drinks market is oligopolistic and brands are differentiated by characteristics and location. We model firms as price-setting multiproduct oligopolists and assume the existence of Nash equilibrium in prices given the nature of product differentiation on two dimensions. Theoretically we take both dimensions of product differentiation as an outcome of long run decisions associated with large sunk costs. Yet we do allow for movements in location to be endogenous in our estimation routine. We wish to model short-run price and quantity movements for each brand. We model demand by aggregating over consumer choice to the product level. Consumers have heterogenous preferences over observables, such as location and other product characteristics (price), and unobservable characteristics. As an outcome of a multiproduct Nash pricing setting equilibrium we simultaneously model marginal costs as a result of observable distribution costs and costs associated with other observable and unobservable product characteristics. Having our demand and cost primitives consistent with a structural model of equilibrium, we are able to construct a Lerner Index for each brand and undertake a welfare analysis.

3.1 Demand

We analyze demand using a discrete choice approach and define a product to be the average consumption of 220 ml of soft carbonates per day. A consumer i decides whether to buy product $j \in J$ in period $t \in T$ (where j in our case is a brand of carbonates) or the outside option. The consumer chooses in each period t the product j that gives her the highest utility u_{ijt} (including the utility for the outside option). On the other side of the market, firms decide on a set of brand prices that maximize their profits. Let F be the set of firms in our market and J the set of all different products produced. Each firm $f \in F$ produces a $J_f \subset J$ subset of products. We write down an individual $i's$ indirect utility, a

random utility model, for product j in period t as,

$$u_{ijt} = \underbrace{-\alpha_1 p_{jt} + x_{jt}^1 \beta + \xi_{jt}}_{\delta_{jt}} + \underbrace{\sigma_A x_{jt}^2 \nu_{it}^A + \sigma_C x_{jt}^2 \nu_{ijt}^C + \sigma_N x_{jt}^2 \nu_{it}^N}_{\mu_{ijt}} + \epsilon_{ijt} \qquad (1)$$

where p_{jt} is the price of product j in period t, x^1 are product characteristics that enter linearly in our estimates, whereas x^2 are those that enter nonlinearly. The subscripts A, C, N stand for *Age*, *Closeness*, and *Normal distribution*, respectively, which individuate our consumers (observed and unobserved) characteristics. This *upla* defines each consumers' taste for quality and sensitivity to prices (product characteristics that enter x^2). The sensitivity to prices reflects individual reactions to a price change are different when drawn from a certain age group or have a different taste for product j depending on whether it is in the nearest store or not (*Closeness).* While consumer demographics and unobservable consumer heterogeneity is only market (t) specific, the interaction of the closeness to stores distribution with price is product (j) specific and can be estimated with far greater degrees of freedom when compared to interactions using market level distributions of consumer characteristics.

Furthermore, since some of the product characteristics are unobserved (ξ_{jt}) to us but are observed by our consumers in their choices, we use instruments to control for their correlation with prices and store coverage.[9]. The error term ϵ_{ijt} (i.i.d. across products and consumers) is assumed to have a type 2 extreme value distribution. Equation (1) shows that the indirect utility function can be decomposed in a mean utility δ_{jt} and a deviation from the mean μ_{ijt} and the error ϵ_{ijt}. This middle term represents the main difference from a basic logit model of consumer heterogeneity. To be complete, our utility for the outside good is written as,

$$u_{i0t} = \underbrace{\xi_{0_t}}_{\delta_{0t}} + \underbrace{\sigma_0 \nu_{i0}}_{\mu_{iot}} + \epsilon_{i0_t} \tag{2}$$

We normalize $\xi_{0_t} = \sigma_0 = 0$. Finally, $\{\alpha, \beta, \sigma\}$ are the parameters of the demand that are going to be estimated. The BLP specification of demand allows different individuals to have different tastes for different product characteristics. In addition, the model can allow for consumer heterogeneity in terms of their response to prices. The random coefficients are designed to capture variations in the substitution patterns. By aggregating over the error component, one recovers a logistic form that defines the probability that individual i buys product j in period t $(f_{ijt}(\cdot))$. If we integrate out over the error distribution of ϵ, the following logistic (conditional on individual characteristics) probability that individual i buys product j in period t is obtained,

$$f_{ijt} = \frac{e^{\delta_{jt}(\cdot)+\mu_{ijt}(\cdot)}}{1 + \sum_{j=1}^{Jt} e^{\delta_{jt}(\cdot)+\mu_{ijt}(\cdot)}} \tag{3}$$

The next step is to aggregate over individuals and calculate each product's estimated market shares. The non-closed solution of this integral requires the use of a simulation procedure. We outline computational methods in the next section. Given the number of consumers in the economy I and integrating over the distributions of individual characteristics, we derive each brands demand function as,

$$q_{jt}(\cdot) = I s_{jt}(p, x, \xi; \theta), \text{ for } jt \in Jt \tag{4}$$

[9] In subsection 4.4 we outline the set of instruments that we use to jointly estimate demand and supply.

3.2 Supply

We assume our marginal costs to be loglinear in the following vector of product characteristics,

$$\ln \frac{dC\left(q_{jt};\cdot\right)}{dq_{jt}} \equiv \ln(mc_{jt}) = w_{jt}\gamma + \omega_{jt}, \tag{5}$$

where we denote with w and ω respectively, the observed and unobserved cost characteristics, and with γ the coefficients to be estimated. In addition to allowing for cost differences coming from observable product characteristics, we also allow for product specific distribution costs. That is costs associated with effective store coverage and due to within stores inventory management. In terms of robustness of the functional form, the key to the goodness of fit is the use of packaging by time dummies. In demand they control for the different seasonal cycles of brands but also the nature of the buy, impulse versus one-stop. In cost packaging by time dummies are also very important due to the differences in glass, plastic and aluminium inputs prices over-time.

3.3 Market Equilibrium

Given the demand system in (4), the profits of multiproduct firm ft are

$$\prod\nolimits_{ft} = \sum_{jt\in J_{ft}} \left(p_{jt} - mc_{jt}\right) q_{jt} \tag{6}$$

Maximizing (6) we get, for every $ft \in Ft$ parent house, the common first order conditions

$$s_{jt}\left(\cdot\right) + \sum_{rt\in J_{ft}} \left(p_{rt} - mc_{rt}\right) \frac{\partial s_{rt}\left(\cdot\right)}{\partial p_{jt}} = 0, jt \in J_{ft} \tag{7}$$

from which we get our price equilibria.

In order to derive the markup relation, we define

$$\Delta_{jtrt} = \begin{cases} \frac{-\partial s_{rt}(\cdot)}{\partial p_{jt}}, & \text{if brands } rt, jt \in J_{ft} \text{ are produced by the same firm} \\ & \text{(therefore } rt, jt \in J_{ft}\text{);} \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

which allow us to explicit the following price-cost markup

$$p_{jt} = mc_{jt} + \underbrace{\Delta^{-1}s}_{markup_{jt}} \tag{9}$$

Our interest in substitution effects, dropping the time subscript to simplify notation, is captured by the own and cross-price elasticities which can be derived from

$$
\begin{aligned}
\frac{\partial s_j(\cdot)}{\partial p_j}\frac{p_j}{s_j} &= \left(\frac{1}{ns}\sum_{i=1}^{ns} f_{ij}\left(1-f_{ij}\right)\underbrace{\left(-\alpha_1+\alpha_2 n_i+\alpha_3 a_i+\alpha_4 c_{ij}\right)}_{\frac{\partial u_{ij}}{\partial p_j}}\right)\frac{p_j}{s_j} \\
\frac{\partial s_j(\cdot)}{\partial p_b}\frac{p_j}{s_b} &= \left(-\frac{1}{ns}\sum_{i=1}^{ns} f_{ij} f_{ib}\underbrace{\left(-\alpha_1+\alpha_2 n_i+\alpha_3 a_i+\alpha_4 c_{ib}\right)}_{\frac{\partial u_{ib}}{\partial p_b}}\right)\frac{p_j}{s_b} \qquad (10)
\end{aligned}
$$

($b \neq j$), where n_i, a_i, c_i are, respectively, simulated values from *Normal*, *Age* and *Closeness* (to shops) distributions.

4 Computational Techniques and Estimation Procedures

BLP at the product level of industry uses exogenous distributions on individual characteristics that are at market level and, whenever disaggregated, sub-market level specific (Petrin (2002)). Undoubtedly a noticeable gain in efficiency would be reached with individual characteristics that are product-level specific. Berry Levinsohn and Pakes (2004) use second choice data that is product level to gain efficiency. We use information on effective store coverage by product to create a distribution of consumer tastes for location. The aim is to embed this into the BLP framework not only to gain efficiency, but also to introduce a dimension of product differentiation that was previously omitted. This is the main contribution of our paper.

4.1 The Distribution of Consumer Distance to the Nearest Shop Carrying Product j

Product j may either be distributed in the nearest shop to consumer i or, our consumer may be forced go travel to find the product. In our simulations (see subsection 4.2) we associate a generic disutility to consumers not finding a product available in their nearest shop. By randomizing over effective store coverage by product j we create a distribution of consumers with and without disutility resulting from each brand's location across retail stores. Since a store, weighted by size, locates where the market is, not covering a store clearly creates distance to a brand for consumers in this catchment area. Our distribution reflects a probability distribution of consumers that find the brand in their nearest shop and others will not and incur disutility. One could try to back out the nature of transportation costs or the number of stores to be searched before finding the product. Yet, empirically we find it is enough to allow for a probability distribution of consumers with and without a location disutility for each product.

Example 1 *This provides an example of how the distribution is created. Each shop is either filled up with all the products or with just a subset of the available set of products. Let's assume a market that hosts* 3 *products* $\{a, b, c\}$ *and* 4 *individuals* $\{I, II, III, IV\}$. *We can map our idea of distance into the following matrix (where* 1 *stands for the availability of the product in a consumer's nearest store):*

$j \backslash i$	I	II	III	IV	
a	1	0	0	0	.25
b	1	1	0	0	.50
c	1	1	1	1	1

From the matrix we see that product a has low coverage, product b medium coverage and product c full coverage of consumers. Our version of shop coverage assumes individuals can either find products without travel costs (closest shop) which we denote as 1, *or not, which we denote as* 0. *In the example individual I finds all three products in her nearest shop and she can (without transportation costs) choose among them. Individual II only finds two products in her closest shop (products b and product c) and is required to go to another shop to find product a. Finally, individuals III and IV just find product c in their nearest shop, and have to travel for products a and b. This disutility for travelling has of course a direct impact in the choice of products individuals have.*[10] *We use*

[10] Let's start with an ideal situation (for consumer I) where the nearest shop to individual I sells all different products and that individual I prefers product a. Suppose now product a is no longer available in that shop and individual I is asked to find the product in another shop. Three possible situations araise:

i) individual I prefers product a even though she has to go to buy it into another shop;
ii) individual I prefers another product $\neq a$ available in the closest shop;
iii) individual I prefers not to buy any product (prefers the outside option).

information on effective shop coverage to generate simulations on the availability of products in each consumer's nearest shop (our Closeness distribution C). We discuss our simulations in the next subsection.

4.2 Simulations

Our individuals have their own age, a personal taste, and get disutility from the lack of product j in their nearest shops.[11] An individual, based on his own characteristics, has therefore a personal perception of the average quality in the market (a benchmark quality) and his own sensitivity to a price change. Since one of the individual attributes that we control for is age, we expect an old age person to have a lower perception of quality and be more sensitive to a price change. We simulate individual i in period t to be a random draw from a multivariate distribution $\nu_{it} = [N_{i1t}, A_{i1t}, D_{i1t}; N_{i2t}, A_{i2t}, D_{i2t}]$.[12] Subscripts $1, 2$ denote individual reaction to a benchmark quality and to the price of the products, respectively. We remind N, A and D to stand, respectively, for draws from a *Normal*, *Age* and *Closeness distribution*. A simplifying assumption is these distributions to be all independent from each other.

The following details the individual attributes that define our simulations;

- We know the numerations of 5-year classes of age (Figure II) for the 1995 Irish population. We use this information to recover the corresponding Age distributions. [13] We then generate ns numbers from a $[0, 1]$ uniform distribution and, each period, associate these numbers to the different intervals of our age distribution. We replace these numbers with one of the ages (randomly chosen) within the corresponding class. In our estimates we normalize age to the maximum age of 100 and demean our age distribution.

- We have information on the (weighted) average shop coverage of product j which assumes values in the interval $[0, 1]$. We define distance ($dist$) as one minus effective store coverage. In our estimates we use as means of

[11] We refer to Nevo (2000, 2001) for further details on simulations over different individual characteristics.

[12] In order to avoid problems in our minimization procedure we censor our multinormal distribution to 99%.

[13] Since the age distribution is almost unchanged in a five-year period, we recover individual variability by just shifting this distribution over time.

our binomials the following normalization of our distance measure

$$\frac{\log(dist)}{\log(dist) + \log(1 - dist)} \tag{11}$$

Figure III shows how our normalization maps distance into a non-linear function of shop coverage. This normalization is aimed to give more weights to higher coverage products which may be thought of as a bonus to higher coverage products. For each product j we draw ns $\{0, 1\}$ values from a binomial having our mean defined in (11).[14] A value of one stands for an individual who finds the product in his nearest shop. In our estimates we demean our Closeness distribution.

- Finally, we finish our genome by giving each individual a specific taste. We draw ns values from a Normal distribution assuming individuals have different perceptions of quality. We also assume ns individuals from a log-normal distribution (properly demeaned) assuming all individuals dislike prices.

The entity we simulate is an individual described by a $3 - uple$ of attributes (Age, Taste, Closeness).

As in BLP we obtain our market shares in two stages. In the first stage we integrate out over the distribution of ϵ and obtain the following logistic (conditional on individual characteristics ν) market share functions

$$f_{ijt} = \frac{e^{\delta_{jt}(\cdot)+\mu_{ijt}(\cdot)}}{1 + \sum_{j=1}^{Jt} e^{\delta_{jt}(\cdot)+\mu_{ijt}(\cdot)}} \tag{12}$$

where δ_{jt} is the mean utility and μ_{ijt} the deviations from the mean (1). The above function can be read as the probability of individual i to buy product j in period t. In the second stage, we aggregate (each period/market) over the distribution of individual characteristics ν (see subsection 4.2) and obtain the market shares

$$s_{jt} = \int f_{jt}(\cdot)\, P_0(d\nu)\,. \tag{13}$$

[14] Suppose brand j is present in 80% of shops (weighted by sales). This leads to a value of shop coverage for brand j and mean of our binomial of 0.8. In this case our ns simulations associated to brand j will give about 80% of ones and 20% of zeros.

where P_0 is the population. The non closed solution of (13) requires a simulation procedure. An immediate simulation procedure simply requires one to replace the population density with its empirical distribution obtained from a set of ns random draws.[15]

$$s_{jt} = \int f_{jt}(\cdot) P_{ns}(d\nu) \cong \frac{1}{ns} \sum_{i=1}^{ns} f_{jt}(\cdot) \tag{14}$$

Product j in period t market share is therefore approximated by the average individual probabilities.The next step is to recover the mean utility component

(δ_{jt}). Since it is not possible to recover (δ_{jt}) analytically, we use (as in BLP) a contraction mapping operator,

$$T_{(S_{nt},P_{nst};\theta)}[\delta_{jt}] \simeq \delta_{jt} + \ln(s_{jt}) - \ln[s_{jt}(\cdot)] \tag{15}$$

where θ includes all the parameters that determine the impact of the distribution of consumer characteristics $\{\alpha, \sigma\}$ as well as the product characteristics, the utility parameters that describe the utility surface β and the marginal costs γ. We partition θ in $\theta = \{\theta_1, \theta_2\}$ where $\theta_1 = \{\beta, \gamma\}$ is the subset of parameters that come out of our objective function and $\theta_2 = \{\alpha, \sigma\}$ the parameters that enter our objective function.[16] S_{nt} is the set of market shares we observe and P_{nst} is the empirical distribution of ns drawn from a P_0 population.

Once computed the mean utilities $\delta_{jt}(\cdot)$ we can back out our demand unobservables,

$$\xi_{jt} = \delta_{jt}(\cdot;\theta_2) - x_{jt}\widehat{\beta} \tag{16}$$

and, using the pricing equation (9), back out the supply unobservables,

$$\omega_{jt} = \ln(mc_{jt}(\cdot;\theta_2)) - w_{jt}\widehat{\gamma}. \tag{17}$$

We assume, as in BLP, our unobservables to satisfy the mean independency property,

$$E\left[\xi_j(\cdot;\theta_0)|z\right] = E\left[\omega_j(\cdot;\theta_0)|z\right] = 0 \tag{18}$$

[15] Of course, we need ns different draws for each market $t \in T$. In our simulations $ns = 100$.

[16] It is possible in this way to separate the set of parameters that enter linearly in our estimations from those that enter non linearly. This let us to use a two step non linear GMM procedure. See Hayashi (2000) for a good reference on GMM.

with $z = [x, w]$ our demand and supply observed product characteristics and θ_0 the true parameters value. We make use of the non linear Nelder-Mead procedure (see Lagarias et al, 1998) to minimize a norm of the non linear GMM function (Hansen, 1982) generated by our imposed moments' condition.[17] Finally, we have all the tools necessary to describe the steps of our computation procedure (iteration numbers are denoted by subscribed squared brackets):

1 Begin with an initial parameters value $\theta_{2[0]} = \left(\alpha_{[0]}, \sigma_{[0]}\right)$ and an initial mean utility vector value $\delta_{[0]}$ (with $\delta_{[0]} = \left(\delta_{1[0]}, ..., \delta_{J[0]}\right)$) then, compute the function of the market shares $\left[f\left(x, p, \delta_{[0]}, \nu; \theta_{2[0]}\right)\right]$ (12) and, subsequently, integrate over individual characteristics to recover the market shares $\left[s\left(x, p, \delta_{[0]}, P_{ns}; \theta_{2[0]}\right)\right]$ (14). Use the obtained market shares (14) in the contraction mapping and get $T_{\left(S_n, P_{ns}, \theta_{[0]}\right)}\left[\delta_{[0]}\right] \equiv \delta_{[1]}$ (15).

2 Repeat step 1) (where θ_2 is always fixed at the starting value $\theta_{2[0]}$) until the contraction mapping converges. Suppose the value of its convergence is $T_{\left(S_n, P_{ns}, \theta_{1[0]}\right)}\left[\delta_{[0]}\right] \equiv \widetilde{\delta}$ then, simultaneously estimate $\widehat{\{\beta, \gamma\}}$ (see 16 and 17) and get the residuals ξ and ω.[18]

3 Apply the Nelder-Mead fixed point minimization to the norm of the non linear GMM function and output $\widehat{\theta_{2[1]}}$.

Repeat steps 1) and 2) above until the Nelder-Mead procedure converges.[19].

4.3 Computing a New Equilibrium

One motivation to estimate structural models is that one can not only understand how the market works (undertake a positive analysis from the estimation of the primitives of the model) but, most importantly, predict how the market will change as a function of changes in exogenous conditions. This process of comparative statics requires re-computing the underlying equilibrium. In our analysis we have so far assumed the existence of an equilibrium (the one observed in the market) and, given that equilibrium, we have computed the set

[17]In our estimates we correct for potential correlation between demand and supply unobservables.

[18]We use a linear GMM to estimate $\left\{\widehat{\beta}, \widehat{\gamma}\right\}$.

[19]We have implemented all our algorithms in Matlab. A Matlab version of the algorithms to estimate the demand side of a random coefficient model is available at the Aviv Nevo's homepage, http://emlab.berkeley.edu/users/nevo/. We have extended those original files to our demand and supply version.

of the optimal parameters to be used for backing out the primitives of the underlying model. Our interest in providing a counterfactual pushes us to go one step further and compute the equilibrium that should follow a particular exogenous shock. Re-computing an equilibrium can be a simple exercise in the case of a small number of firms and linear demand and marginal cost functions. Re-computing an equilibrium gets far more complicated when demand is not linear (marginal costs are backed out through the Lerner index) and firms are multiproduct. No analytical solution then exists. This complexity pushes us to discover an algorithm that solves for the new equilibrium. To our knowledge the previous empirical industrial organization literature dealing with comparative statics has avoided these difficulties either by assuming particular structures to avoid the effect of the strong interdependence among firms (brands), or evaluating the effect of exogenous changes using the primitives from the old equilibrium (Lucas Critique) .

We propose a method to re-compute a new equilibrium in a general setting where firms are multiproduct, demand functions are non-linear, marginal costs are backed out from the augmented Lerner index, and there is no analytical solution. We propose a two stage procedure that particular suits our counterfactual based on a change in the distribution of consumer characteristics that does not affect the short run configuration of the cost function.[20] We use the augmented Lerner index (the augmented elasticity rule) to back-out the new prices (and quantities) of equilibrium. What happens is that although the shock in the distribution of consumer characteristics does not affect directly our short- run configuration of cost function it does, however, create inequalities through its propagation via the markup leading to:

$$\widehat{mc} \gtreqless mc\left(\cdot\right) = p - mup\left(\cdot\right) \tag{19}$$

where $\widehat{mc}$ is the originally estimated marginal cost and $mc\left(p, mup(p, s\left(p, \cdot\right), \cdot, ; \theta)\right)$ the new marginal cost after the exogenous shock took place. Clearly, mc is a function of prices and market shares, given other product characteristics and the parameters of the model. The basic idea is to find the price vector that brings marginal costs back to their previously estimated (actual) value. The full procedure is simply the following constrained profit maximising nonlinear

[20] If the shock is on the supply side an extension of the procedure only requires to compute first of all the new marginal costs from the optimal parameters. These newly computed marginal costs would represent the estimated marginal costs reported in the main text.

programming problem.

$$\begin{aligned} \max_p \pi &= (p - mc)\, q \\ s.t.\ mc(\cdot) &= \widehat{mc} \\ p &\geq 0 \end{aligned} \tag{20}$$

In order to compute the new equilibrium we develop a two stage search algorithm that numerically solves this constrained maximization and deals with the complexity of $mc(\cdot)$. The underlying environment foresees that firms (brands) face the decision of which optimal price to set after the exogenous shock has been realized. We are interested in the dynamics towards the new equilibrium. Firms can start the process of changing prices to converge to the new price equilibrium in the market. Changes in prices are associated with, via the Lerner index, new marginal costs. Unfortunately changes in marginal costs due their own price changes have the following undetermined sign,

$$\frac{\partial mc_j}{\partial p_j} = \underset{+}{\frac{dmc_j}{dp_j}} + \underset{-}{\frac{\partial mc_j}{\partial mup_j}} \underset{?}{\frac{\partial mup_j}{\partial p_j}} + \underset{-}{\frac{\partial mc_j}{\partial mup_j}} \frac{\partial mup_j}{\partial s_j} \underset{-}{\frac{\partial s_j}{\partial p_j}} \tag{21}$$

We are aware of the price interdependence with other firms and but are unaware of the sign of the markup substitution effect. However we observe (estimated) marginal costs and are aware that the right change in prices should give the firm, predictions of marginal cost, via the learner index, that are equal to the old (estimated) value of marginal costs that preceded the exogenous shock. The algorithm that we propose is the following:

Stage one: Nature randomly chooses the set of brands to start with positive or negative price changes.[21] After nature has selected the first movement of the brands, she checks whether brands have $mc()$ not converging to $\widehat{mc}$. Let's call these brands the off-side ones. Nature brings back the off-side brands and, randomly, selects the new movements imposing, this time, the rule that only a lower change in prices (whether positive or negative is dictated by the new selection of the Nature) is possible. Nature therefore punishes the noise created in the system by the off-side brands. Nature keeps on selecting until all brands are moving on-side.

[21] Firms toss a coin in order to decide whether to raise or lower their prices.

Stage two: Given that all brands are on-side, the process of convergence is evaluated. If all brands have a marginal cost, backed out of a system of Lerner indexes, close enough to their actual (estimated) marginal costs the program converges and the obtained prices represent the new equilibrium; if not, the program starts again repeating stage one, keeping track of the old prices (and updated quantities) generated at the end of the previous stage one.

Uniqueness is guaranteed if we have quasiconcavity in the profit functions and quasiconvexity in the constraints evaluated at the new price and quantity outcomes holding the parameters of the surface of the utility and cost function constant, as well as the distribution of product characteristics constant.

4.4 Instruments

A heated debate in the GMM techniques is the choice of optimal instruments. Chamberlain (1986) shows the efficient set of instruments to be equal to the conditional expectation of the derivative of the conditional moment condition with respect to the parameter vector. Unfortunately this conditional expectation is very difficult, if not impossible, to compute. We suggest a simpler method based on the goodness of the fit. Our method computes a R^2 for demand and supply, we choose the set of instruments that provides higher efficiency (higher R^2). Our optimal choice of the instruments is also supported by economic arguments which is outlined in the next subsection.

4.4.1 Demand and Supply Side Instruments

We list and explain the instruments used in our demand and supply estimations. In particular, in demand we allow price, consumer taste for location distribution and interaction with price to be endogenous. On the demand side we need cost shifters that explain price and product specific location that are independent of the demand unobservable.

a) The product characteristics

b) Inventories defined as the number of days to stock out on day of audit given the current rate of sales during the bi-monthly period. Stock-outs do not exist in the data. We interpret inventories as a way to reduce transportation or the distribution costs associated with deliveries. We see it as a cost shifter. This measurement of inventories should not respond to factors observable to the consumer but not the econometrician (e.g. product promotions). See discussion of table 3 in data section.

c) Hausman and Taylor (1981) and Hausman, Leonard and Zona (1994) assume systematic cost factors are common across segments Thus the prices of a firm's products in other segments, after the elimination of segment and firm effects, are driven by common underlying costs correlated with brand price, but uncorrelated with the product specific disturbances in demand and can be used as an instrument. Such a cost shifter proves a good instrument for price.

d) We also use non-price Hausman and Taylor (1981) instruments, where the average effective coverage of stores and inventory levels by firms brands in other segments are instruments in a defined segment. This captures potential cost gains from economies of scope in retail distribution. This is a good instrument for the distribution of consumer taste for location, constructed from the effective store coverage of a product.

e) BLP type instruments: the average and the standard deviation of effective coverage of stores and inventories by other firms within the segment (and outside the segment) of the brand in question. The idea here is that distribution structures of other brands determine the equilibrium short-run pricing within the segment, which is a good instrument for price.

   On the supply side we need instruments for effective store coverage that are independent of the cost unobservable. We use the above a) product characteristics, b) inventories and e) BLP type instruments. The most likely unobservable is the marginal cost of brand specific advertising, as we control for firm attachment effects. We drop the price and non-price Hausman and Taylor (1981) instruments, cost shifters and only use the BLP instruments as demand shifters. Clearly, distribution structures of other brands determine the equilibrium short-run pricing within the segment and we use them as demand shifters to identify the cost function.

5 Results

The results from jointly estimating the demand and cost equations are presented in Table 4. The standard errors have been corrected for potential correlation between demand and supply unobservables. We provide estimates for the parameters of the indirect utility and cost functions. With reference to utility, we estimate the mean effect of our product characteristics (including price) and the parameters that define individual variability towards a benchmark quality and prices. Our specification of the utility and cost function, choices of demand and supply side instruments and our structural model of equilibrium produce good results. The model is simulated to explains 85 per cent of the variation in market share and 75 per cent of the variation in marginal cost across brands and time. In addition, the choice of instruments sets for demand and supply seem to be correct given the value of the GMM objective function.[22].

It is important that we get good estimates of the demand primitives. The coefficient on price and interaction of price with consumer taste distributions will be the focal point. Yet, it will be the quality of the other controls and the instrument set that will give us the ability to obtain efficient estimates of our coefficients on price and interactions with price. We address these control variables first. In terms of the utility function we see that only Orange and Mixed Fruit give higher utility than Cola. Regular sweeter has the advantage over diet. Packaging formats, Cans, 2-litre and Multi-pack seem less popular compared to Standard and 1.5 litre formats. Yet we have extensive packaging by season dummies included. Though not reported the importance of packaging does switch by season. Cans become more important in the summer months and 2-litre is popular during the Christmas period. On average, Standard and 1.5 litre formats have the advantage.

We interact the market level and product level consumer taste distributions with the constant. The unobserved taste structures of consumers that dictate whether they choose the outside good, or not, and the observed taste structure

[22]In terms of robustness of functional forms, the key to the goodness of fit is the use of packaging by time dummies. In demand they control for the different seasonal cycles of brands but also the nature of the the buy, impluse versus one-stop. The interactions of Closeness to Stores distribution with the constant and price come in with and without the other interactions terms reported. Packaging by time dummies are also very important in cost due to the differences in using glass, plastic and aluminium inputs and their pricing over-time. The nature of distribution costs is also an important part of costs functional form.

in terms of age are significant. The product level consumer taste distributions that reflect consumer distance to the nearest store that carries the brand are highly significant. Brands with good coverage of consumers, via effective store coverage, have significantly higher demand over other products inside the market and relative to the outside option.

We now turn to our estimates of our coefficient on price and the interaction of price with our consumer taste distributions. The coefficients on price and its interaction with taste distributions that reflect consumer taste for closeness are highly significant. The market level consumer taste distributions interaction with price are not significant. This will imply that own- and cross-price elasticities will be more responsive when the distribution of consumers distance to stores by product reflect good effective store coverage. We see clearly a trade off between covering the market and the nature of price competition that a brand faces. Less coverage is not a good attribute in terms of market share, but can potentially lead to higher price cost mark-ups by making own- and cross-price elasticities less responsive. Even though the market level interactions do not come in, we will see that our product level consumer taste distribution for geography will have an impact on demand primitives.

The degree of effective store coverage is also an important determinant of brand marginal cost. Marginal cost is increasing with market coverage and decreasing in inventories (controlling inversely for delivery costs to the shops you are in). Brands in 2-litre packaging or multi-packs seem to have lower marginal costs than cans. The production of standard and 1.5 litre formats seems more costly. Lemonade seems to have higher and Mixed Fruit lower marginal costs than either Cola or Orange.

In summary, distributions of consumer taste for product location and it's interaction with price in utility and effective store coverage in cost would have been an important omitted variables. In addition, information on product specific store coverage has been a great source of BLP type instruments in our estimation routine. Yet, how empirically important is product differentiation coming from consumer taste for location in terms of the demand primitives?

We document this in tables 5, 6 and 7 averaging over brands to the Company and Segment level. Given the heterogeneity in brand market coverage within Companies and Segments, we also present the demand primitives for brands with less than (or equal) or greater than 50 per cent of the market covered. What is clear from table 5 is that brands belonging to companies with low market coverage tend to have lower own- and sum of cross- price elasticities. To see that this results from the partial effect of consumer tastes for product location on the demand primitives, we simulate the effect of a 1 per cent increase in market coverage (hence changing the consumer taste distributions) on the primitives, holding the parameter set and all other variables constant (including market shares and prices). We see clearly that the own- and sum of cross-price elasticities become more elastic in response to such an exogenous change in the product level consumer taste for location distributions. This is more pronouced for brands with lower market coverage. This results from our normalization of the mapping of distance into a non linear function of market coverage (see Figure III). This normalization is aimed to give more weight to higher coverage products, however increases in market coverage benefit the low coverage products more. In tables 6 and 7 we undertake the same analysis by our regular and diet segments respectively. The 2 liters and mutlipack brands, across flavour and sweetener segments, have relatively inelastic and similar primitives by market coverage. In contrast, brands packaged by cans or standard packaging, across flavour and sweetener segments, tend to have inelastic primitives as a result of low coverage and relatively elastic with high coverage. Again we simulate the effect of a 1 per cent increase in market coverage, changing the consumer taste distributions for product location, on the primitives, holding the parameter set and all other variables constant. This isolates the effect of market coverage. We see clearly that the own- and sum of cross-price elasticities become more elastic and this is more pronouced for brands with lower market coverage in cans and standard format. In summary, packaging and the consumer taste distribution for product location are important and interesting determinants of the demand primitives. Packaging and distribution costs are also important interesting and important determinants of the cost primitives.

5.1 Market Power

Given the primitives by brand/product we should not be surprised with the estimates of the Lerner index that the structural model produces. Aggregating to the company and segment level, we calculate the price cost mark-ups and profits by market coverage in the last bi-monthly period. Clearly, in table 8, a monotonic relationship between market power and market share does not exist at the company level in this industry. There is a clear premium for brands that operate in a small subset of the stores. Brands of companies with a smaller market share and coverage of the CSD market can extract rents within the product segments and stores of the market they operate in that are comparable to any brand of greater size or market coverage. Its seems that inferring market power from the distribution of market shares is ill advised in multi-product firms differentiated goods industries. In tables 9 and 10 we document the price cost mark-ups, among other factors, by flavor and packaging in regular and diet segments, respectively. Mark-ups (profits) are clearly higher in certain packaging types. It is within these segments that we observe different degrees of market power, and not at the company level. Mark-ups are clearly higher in the 2 litre and in cans multi-packs whose main market is large chain stores. The degree of effective store coverage does not effect market power is the same way as observed in cans and standard packaging. Clearly, brands in cans and standard packaging that target a smaller set of shops has lead to higher mark-ups. Packaging matters. We feel that this reflects store type (chain versus small stores) and nature of buy (impulse versus one-stop).

5.2 Counterfactual

In a counterfactual exercise, holding the parameters of the surface of the utility and cost function constant and the distribution of product characteristics constant, we examine the effects on welfare in an equilibrium that results from a change in the distribution of consumer taste for location distributions. By holding marginal costs fixed we reduce the simulated numbers of consumers having disutility of not having the products in their nearest shop by expanding effective store coverage for each product by one per cent. The numerical method that solved for a new equilibrium in prices and market shares for each brand, fixing marginal cost and the parameter set, was outlined in section 4. This is a non-trivial exercise and is an important innovation of this paper. One motivation for estimating the parameters of the utility and cost function, within a structural model, with as much flexibility (non-linearity) in functional forms as possible, is that it allows one to undertake policy experiments (counterfactuals). Yet if researchers have problems simulating a new equilibrium in price and quantity outcomes due to the nature of the functional forms (the presence of nonlinearities) this goes against the key objective of having a structural model.

We introduce a numerical method that allows the structural model to forecast the effect of a policy change by allowing convergence to a new equilibrium in prices and market shares for all brands and consumers. BLP avoid the issue by undertaking a counterfactural out of sample. Nevo (2000), fixing the demand primitives at the old equilibrium, focuses on which structural models of pricing predicts observable marginal costs the best. This again avoids having demand primitives changing in response to a policy change and the need to move to a new optimal vector of prices and consumer demands.

In tables 11, 12 and 13 we see the results of our counterfactual. Bringing consumers closer to the market for all brands induces all own- and cross-price elasticities in the new equilibrium to become more elastic. We see this at the company and segment level. If we compare these primitives to those in tables 5, 6, and 7 (where no brand could respond with a price change or where no consumer could change their product choice) we see much bigger increases in the own and cross-price elasticities in the new equilibrium.

In tables 15, 16 and 17 we compare welfare before and after the experiment. Inside the market, increases in the own- and cross-price elasticities in the new equilibrium increase price competition but this also induces an expansion effect that brings consumers in from consuming the outside good. This has the effect of expanding demand from an inside market share of 62 to 70 per cent. Overall the expansion effect offsets the effects of increased price competition and results in an increase in aggregate consumer and producer surplus. In tables 16 and 17, even though aggregate producer surplus increases, we see winners and losers across the segments by market coverage. Brands with low market coverage tended to be winners and brands with high coverage tended to be losers within segments as a result of the change in the consumer taste for location distributions. In the new equilibrium the shock to demand generated bigger quantity than price adjustments.

5.3 Conclusion

This paper highlights the role of location in retail markets. Using data for the retail CSD market we demonstrate clear efficiency gains in the estimation of demand and cost primitives, using the BLP estimation routine, by allowing consumers to have preferences over location and products to carry distribution costs, alongside preferences and costs associated with other observable and unobservable product characteristics.

In addition, we highlight the role of packaging. We see clear differences in demand primitives and mark-ups by market coverage across packaging formats. In demand, in the case of the cans and standard format, packaging type reflects impulse buys across small stores. In the 2 litres or multi-pack cans format packaging reflects one-stop buys in supermarket. In cost, packaging controls for the nature of costs in terms of glass, plastic and aluminium input prices. Mark-ups are clearly higher in the 2 litre and in cans multi-packs whose main market is large chain stores. In addition, the degree of effective store coverage does not effect market power is the same way as observed in cans and standard packaging.

As a counterfactual exercise, we show the effects on welfare of an equilibrium that results from increasing the simulated numbers of consumers that have access to products in their nearest store, by expanding effective store coverage for each product by one per cent. We introduce a numerical method that allows the structural model to forecast prices and market shares for all brands in the new equilibrium resulting form this change in the distribution of consumer characteristics. While increases in the own- and cross-price elasticities in the new equilibrium increases the intensity of price competition in the inside market we also see a large market expansion effect as consumers come in from consuming the outside good. Overall, consumer and producer surplus both increase, highlighting the potential role of general equilibrium considerations in industry counterfactuals.

References

[1] Bajari, P., Benkard, C.L. and Levin, J. (2004), "Estimating Dynamic Models of Imperfect Competition," *Mimeograph*, Duke University.

[2] Berry, S. (1994), "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25, pp.242-262.

[3] Berry, S., Levinsohn, J. and A. Pakes, (1995) "Automobile Prices in Market Equilibrium," *Econometrica*, 63, pp841-890.

[4] Berry S., Levinsohn J. and Pakes A. (2004). "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: the New Car Market," *Journal of Political Economy*,112(1), 68-104.

[5] Chamberlain, G. (1986), "Asymptotic Efficiency in Estimation with Conditional Moment Restrictions," *Journal of Econometrics*, 33, 305-334.

[6] d'Aspremont, C., J. Gabszewicz and J. Thisse (1979), "On Hotelling's Stability in Competition", *Econometrica*, vol. 47, no. 5, pp. 1145-50.

[7] Hansen L. (1982). "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, 1029-1054.

[8] Hausman, J. (1978) "Specification Tests in Econometrics," *Econometrica*, 46.

[9] Hausman, J. and W. Taylor (1981), "Panel and Unobservable Individual Effects," *Econometrica*, 49.

[10] Hausman, J., G. Leonard, and J.D. Zona, (1994), "Competitive Analysis with Differentiated Products," *Annales D'Économie et de Statistique*,34, pp159-80.

[11] Hayashi F. (2000). "Econometrics," Princeton University Press.

[12] Hotelling, H. (1929). "Stability in Competition", *Economic Journal.*

[13] Irmen, A. and Thisse, J.F. (1998), "Competition in Multi-Characterisitcs Spaces: Hotelling was almost right," *Journal of Economic Theory*, 78, pp76-101.

[14] Lagarias J. C., Reeds J. A., Wright M. H. and Wright P.E. (1998). "Convergence Properties of the Nelder-Mead Simplex Method in Low Dimensions," *SIAM Journal of Optimization*, 112-147, Vol. 9.

[15] Mariuzzo F., Walsh P. P. and Whelan C. (2003). "Firm Size and Market Power in Carbonated soft Drinks," *Review of Industrial Organization*, 23, pp283-299.

[16] Mariuzzo F., (2004). "Automobile Equilibrium Prices: an Empirical Study on the Italian Market Price Elasticities," Ph.D. Dissertation, Dipartimento di Scienze Economiche, Università di Venezia.

[17] McFadden D. (1989). "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration," in *Econometrica*, 995-1026, Vol. 57, Issue 5.

[18] Nevo A., (2000). "A Practitioners Guide to Estimation of Random Coefficients Logit Models of Demand," *Journal of Economics & Management Strategy*, 513-548, Vol. 9, Issue 4.

[19] Nevo A., (2001). "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, 307-342, Vol. 69, Issue 2.

[20] Pakes A. and Pollard D. (1989). "Simulation and the Asymptotics of Optimization Estimators," *Econometrica*, 1027-1057, Vol.57, Issue 5.

[21] Petrin A. (2002). "Quantifying the Benefits of New Products: the Case of the Minivan," in *Journal of Political Economy*, 110, 705-729.

[22] Salop, S. 1979, "Monopolistic Competition with Outside Goods", *The Bell Journal of Economics*, vol.10, pp.141-156.

[23] Sutton, J., (1991), Sunk Costs and Market Structure: Price Competition, Advertising and the Evolution of Concentration, Cambridge, MA: MIT Press.

[24] Sutton, J. (1998). Technology and Market Structure: Theory and History, Cambridge, MA: MIT Press

[25] Walsh, P.P. and C. Whelan, (1999), "Modelling Price Dispersion as an Outcome of Competition in the Irish Grocery Market", *Journal of Industrial Economics*, XLVII, pp.1-19.

[26] Walsh, P.P. and C. Whelan (2002a), "Portfolio Effects and Firm Size Distribution: Carbonated Soft Drinks," *The Economic and Social Review*, 33, 43-54.

[27] Walsh, P.P. and C. Whelan (2002b), "Product Differentiation and Firm Size Distribution: An Application to Carbonated Soft Drinks" , *Discussion Papers Series EI/31*, STICERD, LSE.

Table 1: Number of Brands (B) and Store Coverage (SC) within Segments, averaged Oct.92-May 97

	Cans		**Standard**		**1.5 Litre**		**2 Litre**		**MultipkCans**	
	B	**SC**	**B**	**SC**	**B**	**SC**	**B**	**SC**	**B**	**SC**
Regular Cola	1	0.99	2	0.83	1	0.90	1	0.78	2	0.53
Regular Orange	2	0.74	1	0.41	2	0.48	2	0.52	2	0.42
Regular Lemonade	2	0.94	3	0.62	2	0.93	2	0.75	2	0.41
Regular Mixed Fruit	2	0.75	2	0.59	1	0.48	2	0.51	1	0.13
Diet Cola	2	0.88	1	0.82	2	0.80	2	0.64	2	0.46
Diet Orange	1	0.10	0		0		1	0.38	0	
Diet Lemonade	2	0.97	1	0.51	2	0.87	2	0.68	2	0.38
Diet Mixed Fruit	1	0.37	0		1	0.10	1	0.38	0	
Coca Cola Bottlers:	**Segments Covered = 35/40**						**Number of Brands = 52**			
Regular Cola	2	0.86	3	0.60	1	0.42	2	0.54	2	0.39
Regular Orange	2	0.93	2	0.70	1	0.76	1	0.61	1	0.43
Regular Lemonade	0		0		0		0		0	
Regular Mixed Fruit	1	0.92	4	0.70	2	0.49	2	0.75	0	
Diet Cola	2	0.64	1	0.20	2	0.13	2	0.42	1	0.32
Diet Orange	2	0.70	1	0.23	1	0.46	1	0.52	0	
Diet Lemonade	0		0		0		0		0	
Diet Mixed Fruit	0		1	0.37	0		0		0	
C & C:	**Segments Covered = 24/40**						**Number of Brands = 45**			
Regular Cola	3	0.22	3	0.60	1	0.14	2	0.62	1	0.03
Regular Orange	2	0.44	5	0.71	2	0.56	2	0.69	1	0.06
Regular Lemonade	2	0.27	3	0.76	2	0.19	2	0.75	0	
Regular Mixed Fruit	3	0.76	9	0.86	4	0.49	3	0.55	0	
Diet Cola	1	0.06	1	0.01	1	0.05	1	0.02	0	
Diet Orange	0		0		0		0		0	
Diet Lemonade	0		0		0		0		0	
Diet Mixed Fruit	1	0.21	1	0.20	0		0		0	
Others:	**Segments Covered = 24/40**						**Number of Brands = 59**			

Table 2: Segments Quantity and Price Levels, Oct'92 prices, averaged Oct.92-May 97

	Brands	Firms	Price Per Litre	Unit Sales Ltr (000)	Unit Sales Shares	Revenue £IR(000)	Revenue Shares
Cola Can	6	5	1.43	1486.39	4.22	2115.8	8.018
Cola Standard	11	5	1.26	1333.49	3.78	1691.9	6.411
Cola 1.5 litre	3	3	0.75	892.60	2.53	671.6	2.545
Cola 2 litre	5	4	0.50	3866.89	10.97	1945.0	7.371
Cola Can Multipacks	5	2	0.96	677.80	1.92	648.4	2.457
Orange Can	6	4	1.38	653.39	1.85	886.7	3.360
Orange Standard	10	6	1.27	741.43	2.10	931.1	3.528
Orange 1.5 litre	5	4	0.68	781.34	2.22	535.0	2.027
Orange 2 litre	5	4	0.46	3000.27	8.51	1382.2	5.238
Orange Can Multipacks	3	3	0.97	174.02	0.49	170.0	0.644
Lemonade Can	4	2	1.41	498.02	1.41	698.9	2.649
Lemonade Standard	5	2	1.16	487.17	1.38	569.3	2.158
Lemonade 1.5 litre	3	2	0.71	1322.93	3.75	939.4	3.560
Lemonade 2 litre	4	2	0.47	4140.18	11.75	1940.7	7.354
Lemonade Can Multipacks	2	1	0.97	127.93	0.36	124.2	0.471
Mixed Fruit Can	7	5	1.39	752.36	2.13	1044.8	3.959
Mixed Fruit Standard	19	10	1.37	2217.30	6.29	3127.8	11.853
Mixed Fruit 1.5 litre	7	6	0.74	633.04	1.80	464.6	1.760
Mixed Fruit 2 litre	8	6	0.41	6612.09	18.76	2634.8	9.985
Mixed Fruit Can Multipacks	1	1	0.83	7.63	0.02	5.9	0.022
Diet Cola Can	4	3	1.39	392.24	1.11	541.7	2.053
Diet Cola Standard	3	3	1.30	328.14	0.93	423.8	1.606
Diet Cola 1.5 litre	4	2	0.75	292.71	0.83	220.6	0.836
Diet Cola 2 litre	4	3	0.55	1005.39	2.85	536.6	2.033
Diet Cola Can Multipacks	3	2	0.96	222.27	0.63	212.9	0.807
Diet Orange Can	2	1	1.27	82.80	0.23	105.5	0.400
Diet Orange Standard	1	1	1.19	15.88	0.05	19.2	0.073
Diet Orange 1.5 litre	1	1	0.71	75.52	0.21	53.9	0.204
Diet Orange 2 litre	3	2	0.56	254.33	0.72	140.9	0.534
Diet Lemonade Can	2	2	1.44	186.00	0.53	267.6	1.014
Diet Lemonade Standard	1	1	1.29	75.24	0.21	95.8	0.363
Diet Lemonade 1.5 litre	1	1	0.73	572.03	1.62	415.0	1.573
Diet Lemonade 2 litre	2	1	0.59	1197.89	3.40	699.1	2.649
Diet Lemonade Can Multipacks	1	1	0.96	74.21	0.21	71.3	0.270
Diet Mixed Fruit Can	2	2	1.27	13.69	0.04	17.5	0.066
Diet Mixed Fruit Standard	2	2	1.17	14.26	0.04	16.9	0.064
Diet Mixed Fruit 1.5 litre	1	1	0.83	0.67	0.00	0.5	0.002
Diet Mixed Fruit 2 litre	1	1	0.55	39.96	0.11	21.7	0.082
Total	**157**	**107**		**35249.48**	**100**	**26388.36**	**100**

Table 3: Segments Store Coverage and Inventory Levels, May'93 (Initial), May'95 (Middle) and May 97(End)

	Coverage Initial	Coverage Middle	Coverage End	Inventories Initial	Inventories Middle	Inventories End
Cola Can	0.95	0.93	0.94	16	16	20
Cola Standard	0.69	0.86	0.89	18	14	16
Cola 1.5 litre	0.84	0.84	0.81	21	16	19
Cola 2 litre	0.68	0.74	0.79	14	12	13
Cola Can Multipacks	0.43	0.49	0.50	16	11	11
Orange Can	0.80	0.80	0.75	25	21	27
Orange Standard	0.81	0.72	0.71	25	16	20
Orange 1.5 litre	0.64	0.65	0.61	22	17	23
Orange 2 litre	0.70	0.61	0.62	13	13	16
Orange Can Multipacks	0.37	0.39	0.43	19	19	14
Lemonade Can	0.91	0.95	0.84	26	18	27
Lemonade Standard	0.81	0.74	0.82	26	18	18
Lemonade 1.5 litre	0.83	0.87	0.87	17	11	15
Lemonade 2 litre	0.76	0.75	0.80	15	12	11
Lemonade Can Multipacks	0.38	0.35	0.40	19	10	16
Mixed Fruit Can	0.87	0.83	0.77	24	18	28
Mixed Fruit Standard	0.92	0.80	0.76	24	17	22
Mixed Fruit 1.5 litre	0.54	0.47	0.41	29	18	26
Mixed Fruit 2 litre	0.68	0.65	0.64	18	10	15
Mixed Fruit Can Multipacks	0.84	0.80	0.04	21	19	3
Diet Cola Can	0.78	0.82	0.88	24	20	23
Diet Cola Standard	0.55	0.76	0.89	15	23	19
Diet Cola 1.5 litre	0.40	0.60	0.75	14	13	21
Diet Cola 2 litre	0.69	0.41	0.68	30	10	13
Diet Cola Can Multipacks	0.51	0.69	0.41	28	21	8
Diet Orange Can	0.45	0.46	0.70	16	23	27
Diet Orange Standard	0.84	0.48	0.52	24	12	22
Diet Orange 1.5 litre	0.84	0.91	0.35	20	16	34
Diet Orange 2 litre	0.60	0.54	0.51	13	13	15
Diet Lemonade Can	0.35	0.85	0.90	21	15	24
Diet Lemonade Standard	0.49	0.73	0.75	26	10	7
Diet Lemonade 1.5 litre	0.01	0.32	0.84	3	8	16
Diet Lemonade 2 litre	0.36	0.22	0.77	20	39	10
Diet Lemonade Can Multipacks	0.95	0.33	0.35	16	7	13
Diet Mixed Fruit Can	0.69	0.93	0.17	18	16	37
Diet Mixed Fruit Standard	0.84	0.86	0.37	21	14	20
Diet Mixed Fruit 1.5 litre	0.68	0.84	0.38	14	16	12
Diet Mixed Fruit 2 litre	0.43	0.74	0.94	16	12	20

Table 4: Estimation of Demand and Marginal Cost Equation: BLP Specification

		Demand	**Cost**
	Variables	**Coefficient (t-stat)**	**Coefficient (t-stat)**
Means			
	Constant	-3.3 (1.4)	0.14 (.45)
	Inventories		-.16 (2.1)*
	Store Coverage		.20 (2.7)*
	Price	-6.8 (2.9)*	
Default Cola	Orange	.71 (2.9)*	.04 (.40)
	Lemonade	.19 (0.8)	.19 (2.2)*
	Mixed Fruit	.74 (2.8)*	-.22 (2.0)*
Default Cans	Standard	3.0 (4.0)*	.41 (2.5)*
	1.5 Litre	3.1 (3.9)*	.37 (2.3)*
	2 Litre	-.76 (1.2)*	-.71 (3.0)*
	Multi-Pack Cans	-2.1 (3.0)*	-1.68 (3.7)*
Default Diet	Regular	.91 (4.8)*	-.05 (.53)
Interactions			
Parametric Distribution	Constant	.76 (1.7)*	
	Price	-0.19 (.18)	
Age Distribution	Constant	-6.7 (2.7)*	
	Price	-5.8 (.53)	
"Closeness to Stores" Distribution	Constant	18.9 (5.5)*	
	Price	-8.8 (3.3)*	
R^2		.85	0.75
# Negative Predicted Mark-Ups			0
GMM Objective		.0076	
# of Simulations		100	
Company Dummies		Yes	Yes
Packaging X Time Dummies		Yes	Yes
Observations		4,645	4,645

Instruments for demand regression: Flavor, Packaging and Diet characteristics and inventories; Hausman-Taylor instrumental variables (brands of the same firm in other segments) with respect to price, store coverage and inventories; BLP instruments (brands of the other firms in the same and others segment) with respect the average and Standard Deviation of store coverage and inventories. Instruments for supply regression the same as demand, expect we drop the Hausman-Taylor instrumental variables.

Table 5: Company Level, Own Price and Sum of Cross Price Elasticties (last period).

Companies	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Coca Cola	33	0.22 <0.5	-7.39	4.99	-7.68	5.23
	23	0.80 > 0.5	-9.86	6.44	-9.88	6.45
C&C	20	0.24 <0.5	-7.64	5.35	-8.07	5.45
	21	0.72 > 0.5	-10.01	6.54	-10.05	6.55
All Others	37	0.12 <0.5	-7.00	4.16	-7.66	4.91
	20	0.67 > 0.5	-8.54	6.23	-8.56	6.27
All Others						
Rank 3	11	0.15 <0.5	-6.25	4.50	-6.33	4.59
	9	0.66 > 0.5	-7.21	6.12	-7.22	6.18
Rank 4	4	0.15 <0.5	-8.47	4.54	-9.13	4.65
	3	0.59 > 0.5	-8.06	6.21	-8.10	6.34
Rank 5	3	0.12 <0.5	-3.73	2.64	-3.74	2.79
	1	0.57 > 0.5	-3.68	5.44	-3.68	5.34
Rank 6	3	0.11 <0.5	-8.22	4.26	-8.16	6.79
	1	0.56 > 0.5	-3.36	5.47	-3.38	5.47
Rank 7	2	0.29 <0.5	-14.50	6.93	-14.77	7.39
	2	0.96 > 0.5	-18.15	7.10	-18.21	7.18
Rank 8	3	0.12 <0.5	-8.11	4.63	-12.11	5.81
	4	0.66 > 0.5	-9.60	6.46	-9.60	6.48
Rank 9	6	0.04 <0.5	-3.99	2.07	-8.15	5.80
Rank 10	1	0.19 <0.5	-11.08	6.74	-11.77	7.28
Rank 11	2	0.02 <0.5	-8.51	3.14	-8.44	3.13
Rank 12	1	0.23 <0.5	-12.17	6.27	-12.34	6.51
Rank 13	1	0.04 <0.5	-2.84	1.09	-2.99	1.10

*Simulated elasticities after a one per cent increase in market coverage.

Table 6: Segment Level, Own Price and Sum of Cross Price Elasticties (last period).

Regular Segments	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Cola Can	3	0.10 <0.5	-7.96	5.14	-12.11	5.59
	3	0.90 > 0.5	-13.57	6.88	-13.61	6.86
Cola Standard	7	0.02 <0.5	-3.21	1.47	-6.06	2.61
	4	0.74 > 0.5	-11.75	6.80	-11.79	6.81
Cola 1.5 litre	2	0.18 <0.5	-4.20	3.62	-4.30	3.65
	1	0.84 > 0.5	-7.38	6.12	-7.39	6.22
Cola 2 litre	1	0.10 <0.5	-5.22	1.58	-5.43	6.42
	4	0.65 > 0.5	-4.64	5.59	-4.73	5.69
Cola Can Multipacks	4	0.30 <0.5	-8.20	5.05	-8.22	5.13
	1	0.54 > 0.5	-8.05	6.44	-8.12	6.54
Orange Can	4	0.19 <0.5	-9.50	5.35	-9.52	5.46
	2	0.84 > 0.5	-13.56	7.03	-13.60	7.97
Orange Standard	6	0.11 <0.5	-7.22	3.39	-10.54	5.92
	4	0.73 > 0.5	-11.80	6.81	-11.80	6.85
Orange 1.5 litre	3	0.33 <0.5	-6.74	6.18	-6.84	6.95
	2	0.67 > 0.5	-6.83	6.11	-6.85	6.22
Orange 2 litre	1	0.13 <0.5	-5.21	6.73	-5.46	6.51
	4	0.63 > 0.5	-4.94	5.66	-4.96	5.65
Orange Can Multipacks	3	0.42 <0.5	-10.40	6.66	-10.31	6.70
Lemonade Can	3	0.04 <0.5	-3.51	2.88	-7.43	4.09
	1	0.87 > 0.5	-14.09	6.96	-14.09	7.02
Lemonade Standard	2	0.05 <0.5	-8.02	3.59	-7.54	3.75
	3	0.76 > 0.5	-11.09	6.73	-11.10	6.74
Lemonade 1.5 litre	2	0.05 <0.5	-6.26	4.14	-6.69	4.96
	1	0.90 > 0.5	-7.08	6.13	-7.09	6.18
Lemonade 2 litre	1	0.04 <0.5	-5.31	6.32	-5.25	5.62
	3	0.70 > 0.5	-4.02	5.57	-4.03	5.58
Lemonade Can Multipacks	2	0.20 <0.5	-5.95	3.79	-5.96	3.92
Mixed Fruit Can	4	0.23 <0.5	-12.73	6.98	-12.87	6.73
	3	0.78 > 0.5	-13.34	6.96	-13.36	7.01
Mixed Fruit Standard	10	0.16 <0.5	-7.44	3.73	-9.05	5.36
	9	0.79 > 0.5	-13.08	6.88	-13.12	6.86
Mixed Fruit 1.5 litre	6	0.27 <0.5	-6.73	5.68	-7.26	6.68
	1	0.74 > 0.5	-7.21	6.23	-7.21	6.13
Mixed Fruit 2 litre	2	0.33 <0.5	-4.80	5.50	-4.75	5.87
	6	0.61 > 0.5	-4.48	5.63	-4.49	5.60
Mixed Fruit Can Multipacks	1	0.04 < 0.5	-7.85	3.28	-7.82	7.09

*Simulated elasticities after a one per cent increase in market coverage.

Table 7: Segment Level, Own Price and Sum of Cross Price Elasticties (last period).

Diet Segments	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Cola Can	2	0.18 <0.5	-5.70	4.01	-5.76	4.94
	2	0.76 > 0.5	-13.43	6.95	-13.53	6.96
Cola Standard	1	0.38 <0.5	-12.15	6.81	-12.11	6.96
	1	0.91 > 0.5	-12.50	6.86	-12.54	6.85
Cola 1.5 litre	3	0.02 <0.5	-3.64	1.55	-3.50	2.30
	1	0.76 > 0.5	-7.30	6.26	-7.33	6.34
Cola 2 litre	3	0.29 <0.5	-3.95	4.16	-4.82	6.56
	1	0.74 > 0.5	-5.24	5.78	-5.26	5.59
Cola Can Multipacks	3	0.36 <0.5	-10.22	6.29	-10.41	6.39
Orange Can	1	0.70 > 0.5	-12.03	6.78	-12.09	7.02
Orange Standard	1	0.52 > 0.5	-11.77	7.00	-11.87	6.83
Orange 1.5 litre	1	0.35 <0.5	-7.02	6.28	-7.05	6.31
Orange 2 litre	2	0.24 <0.5	-5.69	6.44	-5.89	5.97
	1	0.55 > 0.5	-5.51	5.97	-5.58	5.86
Lemonade Can	1	0.01 <0.5	-2.39	1.12	-2.42	1.13
	1	0.90 > 0.5	-13.68	7.02	-13.69	7.06
Lemonade Standard	1	0.75 > 0.5	-12.56	6.98	-12.64	6.91
Lemonade 1.5 litre	1	0.84 > 0.5	-7.00	6.10	-7.00	6.12
Lemonade 2 litre	1	0.03 <0.5	-5.01	7.18	-5.27	7.25
	1	0.77 > 0.5	-5.63	5.83	-5.66	5.84
Lemonade Can Multipacks	1	0.35 <0.5	-9.79	6.12	-9.86	6.20
Mixed Fruit Can	2	0.17 <0.5	-11.51	6.52	-11.64	6.54
Mixed Fruit Standard	2	0.3 <0.5	-11.29	6.77	-11.36	6.87
Mixed Fruit 2 litre	1	0.38 <0.5	-5.41	5.93	-5.45	5.97

*Simulated elasticities after a one per cent decrease in market coverage.

Table 8: Estimated company mark-ups in the last bi-monthly period.

Companies	Market Coverage	Market Share	Price Per Litre	Marginal Cost Per Litre	Mark-Up Per Litre	Profit in £IR(000)
Coca Cola	0.22 <0.5	0.02	0.98	0.69	0.31	237.87
	0.80 > 0.5	0.29	0.98	0.82	0.20	2978.45
C&C	0.24 <0.5	0.01	0.93	0.75	0.23	79.33
	0.72 > 0.5	0.13	0.99	0.87	0.14	945.15
All Others	0.12 <0.5	0.02	1.00	0.76	0.27	128.85
	0.67 > 0.5	0.15	0.85	0.75	0.17	967.43
Inside Market		62%				
All Others						
Rank 3	0.15 <0.5	0.0042	0.67	0.51	0.28	27.06
	0.66 > 0.5	0.0552	0.70	0.60	0.20	352.52
Rank 4	0.15 <0.5	0.0019	1.24	1.02	0.23	15.52
	0.59 > 0.5	0.0190	0.79	0.69	0.14	118.10
Rank 5	0.12 <0.5	0.0038	0.97	0.58	0.37	24.48
	0.57 > 0.5	0.0278	0.36	0.26	0.27	171.49
Rank 6	0.11 <0.5	0.0059	0.75	0.65	0.18	39.17
	0.56 > 0.5	0.0237	0.33	0.23	0.30	145.62
Rank 7	0.29 <0.5	0.0013	1.47	1.37	0.07	8.45
	0.96 > 0.5	0.0160	1.89	1.78	0.06	106.28
Rank 8	0.12 <0.5	0.0001	1.18	0.92	0.20	0.93
	0.66 > 0.5	0.0120	0.94	0.84	0.12	73.41
Rank 9	0.04 <0.5	0.0007	1.00	0.61	0.45	6.87
Rank 10	0.19 <0.5	0.0002	1.08	0.99	0.09	1.03
Rank 11	0.02 <0.5	0.0001	1.42	1.08	0.24	2.59
Rank 12	0.23 <0.5	0.0001	1.18	1.08	0.08	0.48
Rank 13	0.04 <0.5	0.0001	1.87	1.21	0.35	2.27

Table 9: Estimated regular segment mark-ups in the last bi-monthly period.

Regular Segments	Market Coverage	Market Share	Price Per Litre	MC Per Litre	Mark-up	Profit in £IR(000)
Cola Can	0.10 <0.5	0.00081	1.19	1.09	0.09	5.19
	0.90 > 0.5	0.02237	1.37	1.23	0.10	235.05
Cola Standard	0.02 <0.5	0.00015	1.33	0.79	0.47	4.70
	0.74 > 0.5	0.02757	1.18	1.05	0.11	277.65
Cola 1.5 litre	0.18 <0.5	0.00077	0.60	0.32	0.53	5.93
	0.84 > 0.5	0.01265	0.72	0.56	0.23	128.87
Cola 2 litre	0.10 <0.5	0.00017	0.42	0.34	0.19	0.85
	0.65 > 0.5	0.07912	0.45	0.33	0.27	720.88
Cola Can Multipacks	0.30 <0.5	0.00373	0.96	0.72	0.28	34.52
	0.54 > 0.5	0.00971	0.80	0.63	0.21	102.83
Orange Can	0.19 <0.5	0.00200	1.16	0.92	0.21	14.59
	0.84 > 0.5	0.00738	1.36	1.21	0.11	64.26
Orange Standard	0.11 <0.5	0.00081	1.34	1.13	0.17	7.07
	0.73 > 0.5	0.01522	1.17	1.05	0.11	117.46
Orange 1.5 litre	0.33 <0.5	0.00202	0.65	0.52	0.20	17.23
	0.67 > 0.5	0.00905	0.66	0.55	0.16	60.95
Orange 2 litre	0.13 <0.5	0.00139	0.54	0.36	0.32	15.23
	0.63 > 0.5	0.04289	0.47	0.36	0.26	301.44
Orange Can Multipacks	0.42 <0.5	0.00384	1.02	0.87	0.16	34.53
Lemonade Can	0.04 <0.5	0.00025	0.85	0.45	0.48	3.22
	0.87 > 0.5	0.00567	1.42	1.24	0.12	62.60
Lemonade Standard	0.05 <0.5	0.00030	1.52	1.08	0.27	3.34
	0.76 > 0.5	0.01143	1.10	0.97	0.12	106.00
Lemonade 1.5 litre	0.05 <0.5	0.00063	0.58	0.48	0.17	4.04
	0.90 > 0.5	0.01498	0.69	0.53	0.23	152.79
Lemonade 2 litre	0.04 <0.5	0.00013	0.50	0.33	0.35	1.39
	0.70 > 0.5	0.06220	0.39	0.27	0.31	558.88
Lemonade Can Multipacks	0.20 <0.5	0.00111	1.02	0.63	0.37	11.89
Mixed Fruit Can	0.23 <0.5	0.00105	1.29	1.16	0.11	9.74
	0.78 > 0.5	0.00849	1.33	1.20	0.10	69.01
Mixed Fruit Standard	0.16 <0.5	0.00866	1.15	0.85	0.25	63.79
	0.79 > 0.5	0.04026	1.32	1.20	0.10	288.25
Mixed Fruit 1.5 litre	0.27 <0.5	0.00749	0.73	0.56	0.31	58.05
	0.74 > 0.5	0.00244	0.69	0.59	0.14	14.83
Mixed Fruit 2 litre	0.33 <0.5	0.00259	0.45	0.32	0.28	19.87
	0.61 > 0.5	0.12114	0.43	0.32	0.27	819.83
Mixed Fruit Can Multipack	0.04 < 0.5	0.00004	0.72	0.59	0.18	0.32

Table 10: Estimated diet segment mark-ups in the last bi-monthly period.

Diet Segments	Market Coverage	Market Share	Price Per Litre	MC Per Litre	Mark-up	Profit in £IR(000)
Cola Can	0.18 <0.5	0.00050	1.06	0.69	0.33	6.40
	0.76 > 0.5	0.00587	1.34	1.20	0.11	63.30
Cola Standard	0.38 <0.5	0.00027	1.19	1.07	0.10	2.04
	0.91 > 0.5	0.00678	1.26	1.08	0.14	73.98
Cola 1.5 litre	0.02 <0.5	0.00010	0.68	0.32	0.54	0.98
	0.76 > 0.5	0.00505	0.71	0.54	0.23	51.76
Cola 2 litre	0.29 <0.5	0.00363	0.47	0.24	0.54	33.15
	0.74 > 0.5	0.01737	0.51	0.35	0.31	171.10
Cola Can Multipacks	0.36 <0.5	0.00495	1.02	0.86	0.16	50.56
Orange Can	0.70 > 0.5	0.00123	1.18	1.06	0.10	9.24
Orange Standard	0.52 > 0.5	0.00079	1.17	1.05	0.10	6.09
Orange 1.5 litre	0.35 <0.5	0.00077	0.68	0.56	0.17	5.66
Orange 2 litre	0.24 <0.5	0.00110	0.56	0.42	0.25	10.31
	0.55 > 0.5	0.00353	0.53	0.41	0.22	25.43
Lemonade Can	0.01 <0.5	0.00001	1.40	0.74	0.47	0.47
	0.90 > 0.5	0.00287	1.37	1.20	0.13	31.64
Lemonade Standard	0.75 > 0.5	0.00270	1.26	1.08	0.14	29.66
Lemonade 1.5 litre	0.84 > 0.5	0.00858	0.67	0.51	0.24	86.65
Lemonade 2 litre	0.03 <0.5	0.00004	0.52	0.33	0.36	0.45
	0.77 > 0.5	0.02603	0.56	0.40	0.29	260.59
Lemonade Can Multipacks	0.35 <0.5	0.00043	0.95	0.78	0.17	4.39
Mixed Fruit Can	0.17 <0.5	0.00014	1.14	1.00	0.12	1.44
Mixed Fruit Standard	0.3 <0.5	0.00040	1.12	1.01	0.10	2.97
Mixed Fruit 2 litre	0.38 <0.5	0.00118	0.52	0.36	0.31	11.74
	0.18 <0.5	0.00050	1.06	0.69	0.33	6.40

Table 11: Company Level, Own Price and Sum of Cross Price Elasticties (last period).

Companies	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Coca Cola	33	0.22 <0.5	-7.39	4.99	-16.98	9.42
	23	0.80 > 0.5	-9.86	6.44	-10.30	6.43
C&C	20	0.24 <0.5	-7.64	5.35	-14.22	7.28
	21	0.72 > 0.5	-10.01	6.54	-8.96	5.86
All Others	37	0.12 <0.5	-7.00	4.16	-12.05	8.83
	20	0.67 > 0.5	-8.54	6.23	-16.09	9.23
All Others						
Rank 3	11	0.15 <0.5	-6.25	4.50	-12.69	9.46
	9	0.66 > 0.5	-7.21	6.12	-7.33	6.65
Rank 4	4	0.15 <0.5	-8.47	4.54	-13.13	5.46
	3	0.59 > 0.5	-8.06	6.21	-3.68	2.97
Rank 5	3	0.12 <0.5	-3.73	2.64	-8.96	4.64
	1	0.57 > 0.5	-3.68	5.44	-3.76	5.31
Rank 6	3	0.11 <0.5	-8.22	4.26	-8.11	9.86
	1	0.56 > 0.5	-3.36	5.47	-6.53	10.73
Rank 7	2	0.29 <0.5	-14.50	6.93	-7.47	4.02
	2	0.96 > 0.5	-18.15	7.10	-9.17	6.02
Rank 8	3	0.12 <0.5	-8.11	4.63	-7.87	3.50
	4	0.66 > 0.5	-9.60	6.46	-12.01	7.94
Rank 9	6	0.04 <0.5	-3.99	2.07	-5.22	2.97
Rank 10	1	0.19 <0.5	-11.08	6.74	-12.62	5.77
Rank 11	2	0.02 <0.5	-8.51	3.14	-11.78	2.77
Rank 12	1	0.23 <0.5	-12.17	6.27	-11.01	6.17
Rank 13	1	0.04 <0.5	-2.84	1.09	-6.66	2.29

*Simulated elasticities after a one per cent increase in market coverage in the new market Equilibrium.

Table 12: Segment Level, Own Price and Sum of Cross Price Elasticties (last period).

Regular Segments	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Cola Can	3	0.10 <0.5	-7.96	5.14	-4.14	2.64
	3	0.90 > 0.5	-13.57	6.88	-18.34	9.19
Cola Standard	7	0.02 <0.5	-3.21	1.47	-8.55	3.30
	4	0.74 > 0.5	-11.75	6.80	-8.54	4.89
Cola 1.5 litre	2	0.18 <0.5	-4.20	3.62	-9.88	7.04
	1	0.84 > 0.5	-7.38	6.12	-4.24	3.59
Cola 2 litre	1	0.10 <0.5	-5.22	1.58	-1.19	1.70
	4	0.65 > 0.5	-4.64	5.59	-3.90	4.87
Cola Can Multipacks	4	0.30 <0.5	-8.20	5.05	-13.90	7.05
	1	0.54 > 0.5	-8.05	6.44	-5.33	4.10
Orange Can	4	0.19 <0.5	-9.50	5.35	-11.23	5.96
	2	0.84 > 0.5	-13.56	7.03	-18.57	9.57
Orange Standard	6	0.11 <0.5	-7.22	3.39	-24.37	8.17
	4	0.73 > 0.5	-11.80	6.81	-8.70	5.06
Orange 1.5 litre	3	0.33 <0.5	-6.74	6.18	-2.68	2.37
	2	0.67 > 0.5	-6.83	6.11	-3.00	2.67
Orange 2 litre	1	0.13 <0.5	-5.21	6.73	-5.10	5.10
	4	0.63 > 0.5	-4.94	5.66	-4.87	6.00
Orange Can Multipacks	3	0.42 <0.5	-10.40	6.66	-13.08	10.21
Lemonade Can	3	0.04 <0.5	-3.51	2.88	-8.97	6.55
	1	0.87 > 0.5	-14.09	6.96	-18.90	9.42
Lemonade Standard	2	0.05 <0.5	-8.02	3.59	-7.32	3.20
	3	0.76 > 0.5	-11.09	6.73	-7.02	4.25
Lemonade 1.5 litre	2	0.05 <0.5	-6.26	4.14	-10.66	5.68
	1	0.90 > 0.5	-7.08	6.13	-3.77	3.29
Lemonade 2 litre	1	0.04 <0.5	-5.31	6.32	-1.59	1.68
	3	0.70 > 0.5	-4.02	5.57	-4.66	6.26
Lemonade Can Multipacks	2	0.20 <0.5	-5.95	3.79	-11.44	9.08
Mixed Fruit Can	4	0.23 <0.5	-12.73	6.98	-8.24	4.21
	3	0.78 > 0.5	-13.34	6.96	-15.93	10.49
Mixed Fruit Standard	10	0.16 <0.5	-7.44	3.73	-7.29	3.91
	9	0.79 > 0.5	-13.08	6.88	-19.23	12.50
Mixed Fruit 1.5 litre	6	0.27 <0.5	-6.73	5.68	-8.08	8.03
	1	0.74 > 0.5	-7.21	6.23	-5.01	4.27
Mixed Fruit 2 litre	2	0.33 <0.5	-4.80	5.50	-5.23	7.61
	6	0.61 > 0.5	-4.48	5.63	-5.97	7.66
Mixed Fruit Can Multipacks	1	0.04 < 0.5	-7.85	3.28	-7.46	2.42

*Simulated elasticities in the new market Equilibrium.

Table 13: Segment Level, Own Price and Sum of Cross Price Elasticties (last period).

Diet Segments	Brands	Market Coverage	Own Price Elasticity	Cross Price Elasticities	Own Price Elasticities*	Cross Price Elasticities*
Cola Can	2	0.18 <0.5	-5.70	4.01	-8.30	4.17
	2	0.76 > 0.5	-13.43	6.95	-15.99	8.21
Cola Standard	1	0.38 <0.5	-12.15	6.81	-4.63	2.66
	1	0.91 > 0.5	-12.50	6.86	-12.65	6.92
Cola 1.5 litre	3	0.02 <0.5	-3.64	1.55	-12.62	3.69
	1	0.76 > 0.5	-7.30	6.26	-3.80	3.29
Cola 2 litre	3	0.29 <0.5	-3.95	4.16	-2.10	2.53
	1	0.74 > 0.5	-5.24	5.78	-5.47	5.83
Cola Can Multipacks	3	0.36 <0.5	-10.22	6.29	-14.88	12.83
Orange Can	1	0.70 > 0.5	-12.03	6.78	-8.05	4.75
Orange Standard	1	0.52 > 0.5	-11.77	7.00	-6.65	3.82
Orange 1.5 litre	1	0.35 <0.5	-7.02	6.28	-3.55	3.16
Orange 2 litre	2	0.24 <0.5	-5.69	6.44	-2.26	2.27
	1	0.55 > 0.5	-5.51	5.97	-6.44	6.73
Lemonade Can	1	0.01 <0.5	-2.39	1.12	-13.04	5.72
	1	0.90 > 0.5	-13.68	7.02	-16.25	8.40
Lemonade Standard	1	0.75 > 0.5	-12.56	6.98	-8.95	4.91
Lemonade 1.5 litre	1	0.84 > 0.5	-7.00	6.10	-4.23	3.70
Lemonade 2 litre	1	0.03 <0.5	-5.01	7.18	-1.45	1.99
	1	0.77 > 0.5	-5.63	5.83	-9.07	9.37
Lemonade Can Multipacks	1	0.35 <0.5	-9.79	6.12	-4.81	3.02
Mixed Fruit Can	2	0.17 <0.5	-11.51	6.52	-5.37	3.26
Mixed Fruit Standard	2	0.3 <0.5	-11.29	6.77	-4.71	2.85
Mixed Fruit 2 litre	1	0.38 <0.5	-5.41	5.93	-4.17	4.57

*Simulated elasticities in the new market Equilibrium.

Table 14: Welfare Counterfactual: Company Level in the last bi-monthly period.

Companies	Market Share	Market Share*	Mark-up	Mark-up*	Profit in £IR(000)	Profit in £IR(000)*	Consumer Surplus £IR(000)	Consumer Surplus £IR(000)*
Coca Cola	0.02	0.04	0.31	0.32	237.9	407.4	213.1	225.7
	0.29	0.29	0.20	0.20	2978.4	2946.4	1636.1	1661.2
C&C	0.01	0.02	0.23	0.23	79.3	168.8	125.4	125.4
	0.13	0.14	0.14	0.15	945.1	990.1	739.7	771.0
All Others	0.02	0.06	0.27	0.28	128.8	401.1	300.9	344.8
	0.15	0.15	0.17	0.17	967.4	919.6	909.0	833.7
Inside Market	***62%***	***70%***			***5337.1***	***5833.4***	***3924.2***	***3961.8***
All Others								
Rank 3	0.0042	0.00510	0.28	0.28	27.06	31.78	31.34	25.07
	0.0552	0.04830	0.20	0.20	352.52	303.58	282.09	275.82
Rank 4	0.0019	0.00830	0.23	0.22	15.52	54.09	37.61	50.15
	0.0190	0.04260	0.14	0.15	118.10	272.37	275.82	244.48
Rank 5	0.0038	0.03600	0.37	0.40	24.48	246.13	162.99	206.87
	0.0278	0.02750	0.27	0.28	171.49	171.00	150.45	156.72
Rank 6	0.0059	0.00390	0.18	0.16	39.17	25.73	43.88	25.07
	0.0237	0.01210	0.30	0.30	145.62	71.83	112.84	68.96
Rank 7	0.0013	0.00200	0.07	0.07	8.45	13.09	12.54	12.54
	0.0160	0.00600	0.06	0.06	106.28	38.42	31.34	31.34
Rank 8	0.0001	0.00030	0.20	0.20	0.93	1.94	0.00	0.00
	0.0120	0.01040	0.12	0.12	73.41	62.38	56.42	56.42
Rank 9	0.0007	0.00270	0.45	0.45	6.87	17.86	6.27	18.81
Rank 10	0.0002	0.00070	0.09	0.09	1.03	4.37	6.27	6.27
Rank 11	0.0001	0.00010	0.24	0.29	2.59	4.42	0.00	0.00
Rank 12	0.0001	0.00010	0.08	0.08	0.48	0.59	0.00	0.00
Rank 13	0.0001	0.00000	0.35	0.40	2.27	1.08	0.00	0.00

Table 15: Welfare Counterfactual: Regular Segment in the last bi-monthly period.

Regular Segments	Market Share	Market Share*	Mark-up	Mark-up*	Profit in £IR(000)	Profit in £IR(000)*	Consumer Surplus £IR(000)	Consumer Surplus £IR(000)*
Cola Can	0.00081	0.0022	0.09	0.11	5.2	16.2	6.3	12.5
	0.02237	0.0120	0.10	0.10	235.1	117.8	75.2	75.2
Cola Standard	0.00015	0.0002	0.47	0.48	4.7	4.0	0.0	0.0
	0.02757	0.0292	0.11	0.11	277.7	272.6	188.1	169.3
Cola 1.5 litre	0.00077	0.0024	0.53	0.53	5.9	17.8	12.5	12.5
	0.01265	0.0220	0.23	0.23	128.9	221.2	131.6	125.4
Cola 2 litre	0.00017	0.0006	0.19	0.21	0.8	4.0	0.0	6.3
	0.07912	0.0779	0.27	0.28	720.9	675.9	438.8	445.1
Cola Can Multipacks	0.00373	0.0054	0.28	0.29	34.5	39.8	31.3	25.1
	0.00971	0.0148	0.21	0.21	102.8	150.9	94.0	81.5
Orange Can	0.00200	0.0026	0.21	0.22	14.6	19.7	12.5	18.8
	0.00738	0.0051	0.11	0.11	64.3	46.1	31.3	31.3
Orange Standard	0.00081	0.0060	0.17	0.17	7.1	41.5	31.3	31.3
	0.01522	0.0223	0.11	0.11	117.5	174.9	144.2	125.4
Orange 1.5 litre	0.00202	0.0063	0.20	0.20	17.2	50.6	31.3	31.3
	0.00905	0.0269	0.16	0.17	60.9	177.9	163.0	156.7
Orange 2 litre	0.00139	0.0015	0.32	0.33	15.2	14.7	6.3	6.3
	0.04289	0.0441	0.26	0.26	301.4	319.2	250.7	244.5
Orange Can Multipacks	0.00384	0.0063	0.16	0.16	34.5	55.1	37.6	37.6
Lemonade Can	0.00025	0.0011	0.48	0.48	3.2	6.9	6.3	6.3
	0.00567	0.0042	0.12	0.13	62.6	46.3	25.1	25.1
Lemonade Standard	0.00030	0.0005	0.27	0.29	3.3	5.9	0.0	0.0
	0.01143	0.0183	0.12	0.12	106.0	166.8	100.3	106.6
Lemonade 1.5 litre	0.00063	0.0004	0.17	0.17	4.0	2.4	0.0	0.0
	0.01498	0.0282	0.23	0.24	152.8	282.0	144.2	156.7
Lemonade 2 litre	0.00013	0.0004	0.35	0.36	1.4	4.3	0.0	0.0
	0.06220	0.0515	0.31	0.32	558.9	442.6	250.7	288.4
Lemonade Can Multipacks	0.00111	0.0020	0.37	0.38	11.9	20.7	12.5	12.5
Mixed Fruit Can	0.00105	0.0022	0.11	0.11	9.7	19.1	18.8	18.8
	0.00849	0.0056	0.10	0.10	69.0	46.8	31.3	31.3
Mixed Fruit Standard	0.00866	0.0436	0.25	0.26	63.8	302.0	206.9	257.0
	0.04026	0.0424	0.10	0.10	288.2	322.0	231.9	231.9
Mixed Fruit 1.5 litre	0.00749	0.0086	0.31	0.30	58.0	69.4	50.1	50.1
	0.00244	0.0035	0.14	0.14	14.8	20.9	18.8	18.8
Mixed Fruit 2 litre	0.00259	0.0033	0.28	0.29	19.9	29.2	18.8	18.8
	0.12114	0.0876	0.27	0.27	819.8	591.7	507.8	495.2
Mixed Fruit Can Multipacks	0.00004	0.0002	0.18	0.19	0.3	2.2	0.0	0.0

Table 16: Welfare Counterfactual: Diet Segment in the last bi-monthly period.

Diet Segments	Market Share	Market Share*	Mark-up	Mark-up*	Profit in £IR(000)	Profit in £IR(000)*	Consumer Surplus £IR(000)	Consumer Surplus £IR(000)*
Cola Can	0.00050	0.0050	0.33	0.34	6.4	51.7	31.3	31.3
	0.00587	0.0038	0.11	0.11	63.3	38.9	25.1	25.1
Cola Standard	0.00027	0.0007	0.10	0.10	2.0	5.3	6.3	6.3
	0.00678	0.0067	0.14	0.14	74.0	71.2	43.9	37.6
Cola 1.5 litre	0.00010	0.0002	0.54	0.55	1.0	1.4	0.0	0.0
	0.00505	0.0098	0.23	0.23	51.8	97.3	56.4	56.4
Cola 2 litre	0.00363	0.0070	0.54	0.54	33.2	59.7	31.3	37.6
	0.01737	0.0167	0.31	0.31	171.1	158.5	94.0	94.0
Cola Can Multipacks	0.00495	0.0063	0.16	0.16	50.6	62.7	43.9	37.6
Orange Can	0.00123	0.0018	0.10	0.11	9.2	14.0	12.5	12.5
Orange Standard	0.00079	0.0014	0.10	0.11	6.1	11.0	6.3	6.3
Orange 1.5 litre	0.00077	0.0015	0.17	0.18	5.7	11.4	6.3	6.3
Orange 2 litre	0.00110	0.0027	0.25	0.26	10.3	24.6	12.5	12.5
	0.00353	0.0031	0.22	0.23	25.4	22.1	18.8	18.8
Lemonade Can	0.00001	0.0000	0.47	0.50	0.5	0.1	0.0	0.0
	0.00287	0.0024	0.13	0.13	31.6	26.1	12.5	12.5
Lemonade Standard	0.00270	0.0038	0.14	0.14	29.7	40.8	25.1	18.8
Lemonade 1.5 litre	0.00858	0.0142	0.24	0.24	86.6	141.3	81.5	81.5
Lemonade 2 litre	0.00004	0.0001	0.36	0.36	0.4	1.6	0.0	0.0
	0.02603	0.0163	0.29	0.29	260.6	159.3	81.5	94.0
Lemonade Can Multipacks	0.00043	0.0009	0.17	0.18	4.4	8.8	6.3	6.3
Mixed Fruit Can	0.00014	0.0003	0.12	0.12	1.4	2.5	0.0	0.0
Mixed Fruit Standard	0.00040	0.0009	0.10	0.10	3.0	6.6	6.3	6.3
Mixed Fruit 2 litre	0.00118	0.0015	0.31	0.31	11.7	15.1	12.5	6.3

Figure I: Bi-monthly sales of Carbonated Soft Drinks by Packaging Type

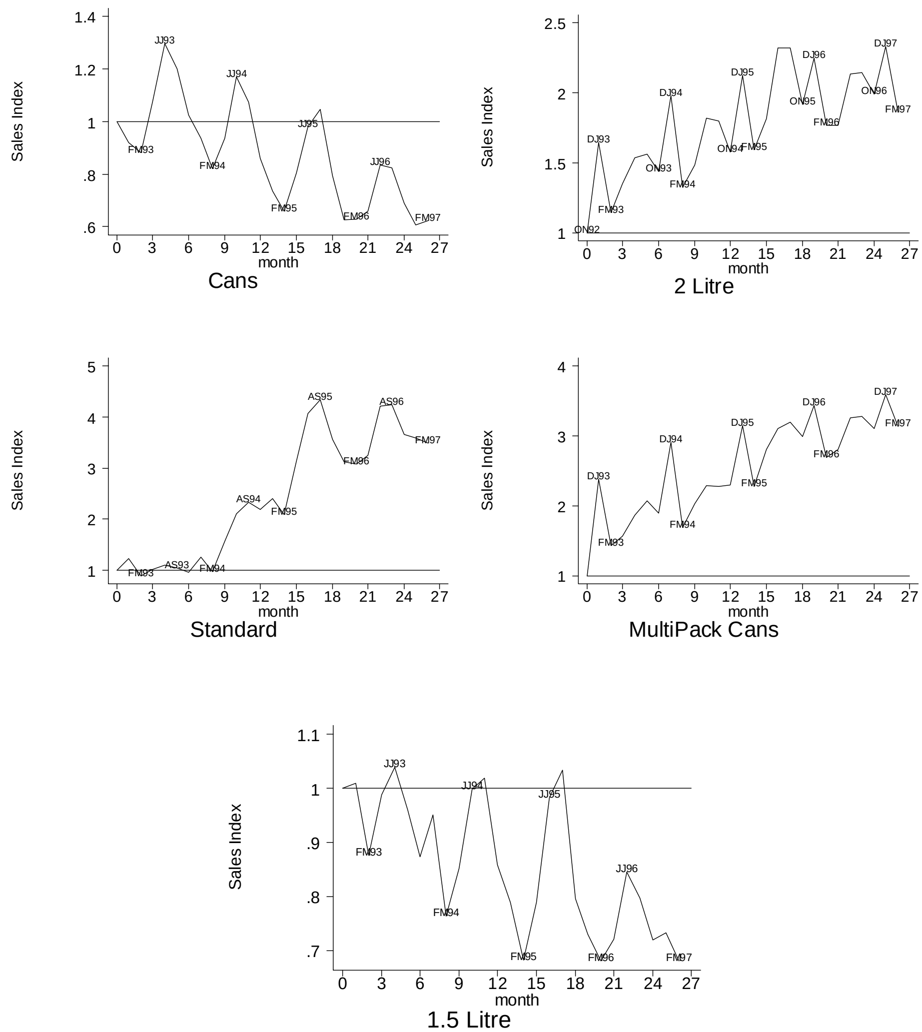

Figure II: Age Distribution

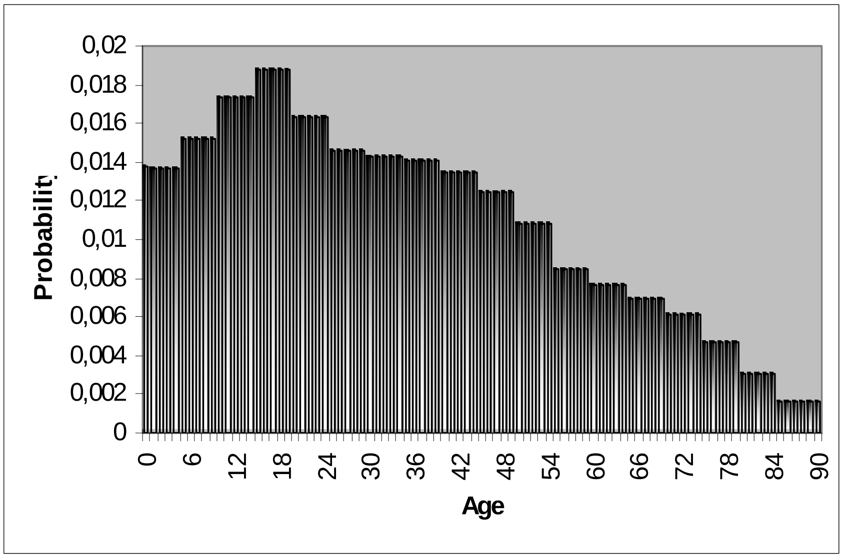

Figure III: Distance normalization