



## Firm Size and Market Power in Carbonated Soft Drinks

FRANCO MARIUZZO<sup>1</sup>, PATRICK PAUL WALSH<sup>2</sup> and CIARA WHELAN<sup>3</sup>

<sup>1</sup>*Department of Economics, University of Venice, Italy;* <sup>2</sup>*Department of Economics, Trinity College, Dublin, Ireland. Email: ppwalsh@tcd.ie;* <sup>3</sup>*Department of Economics, University College Dublin, Ireland*

**Abstract.** Sutton (1998) offers us a simple way to model firm size distributions across differentiated products industries. We analyse the implications of this approach for company markups using a structural model for a specific industry. We incorporate the complexities of multi-product (brand) companies operating with different (strategic) configurations of product characteristics and stores to estimate brand markups, using Irish AC Nielsen retail data for Carbonated Soft Drinks. As a second step we estimate that market power does not increase in companies with higher market share, controlling for other factors. This challenges a traditional mind-set.

**Key words:** Company size and market power, differentiated products.

**JEL Classification:** L11, L25, L66 and L81

### I. Introduction

A belief in a mapping of firm market share into market power has a long history and is still at the centre of most merger investigations. One could argue that a positive relationship is a good rule of thumb in homogenous goods industries.<sup>1</sup> Allowing for multi-product production with goods differentiated by product characteristics *and* store coverage, we show that using such a rule of thumb is ill-advised in retail Carbonated Soft Drinks.

Section II applies Sutton (1998) to show that differences in market shares in retail Carbonated Soft Drinks result mainly from firms having a different number of product and location segments covered by brands, and not from market share heterogeneity within segments. Market shares within product and location segments suggest that small companies, even though they cover less of the market, may have localized power. The aim of this paper is to investigate whether such a

---

<sup>1</sup> Game theoretic models suggest that market share and power in homogenous goods industries can be positively related, though not necessarily so. The relationship is augmented by market conduct. Techniques are available to empirically identify market conduct in homogenous goods industries (Bresnahan, 1989 and 1982; Genesove and Mullin, 1998).

market structure results in small companies extracting brand markups at least as high as large companies.

In Section III we estimate demand and infer brand markups using the structural model of Berry (1994), with some innovations in specification and identification. Using a second step estimator we show that estimated brand markups (and hence company markups in aggregate) do not increase in companies with greater market share, controlling for other factors. The strategic placing of brands across product and store space creates dispersion in market shares but we estimate that it has the effect of narrowing the disparity in market power across companies.

## II. Firm Size in Differentiated Goods

The Sutton (1998) framework marries a game theoretic approach on firm growth with elements of the stochastic approach.<sup>2</sup> Firm growth is modelled as a collection of discrete opportunities, which arrive over an infinite period as an outcome of a stochastic process. These opportunities can reflect openings in new product lines or geographic markets. The limiting firm size distribution is an outcome of deterministic entry games among active firms and potential entrants across opportunities. To model a lower bound on the size distribution of firms Sutton (1998) assumes opportunities of the same size and imposes a *Symmetry Principle* on the form of the entry game into each of these opportunities. In the limit, the firm size distribution is restricted to a lower bound Lorenz curve, with a measure of inequality that is approximately equal to a Gini coefficient of 0.5. This graphs the fraction of top  $k$  ranking firms in the population  $N$  of firms ( $k/N$ ) against their corresponding share of market sales given by the  $k$ -firm concentration ratio ( $C_k$ ) that satisfies,

$$C_k \geq \frac{k}{N} \left( 1 - \ln \frac{k}{N} \right) \quad (1)$$

where the size of the market is the total number of opportunities captured by all firms, and the size of each firm is total number of opportunities captured by the firm. The number of opportunities captured during industry evolution should explain most of the observed firm size distribution, which will be greater than or equal to Sutton's (1998) mathematically-derived lower bound.<sup>3</sup> Empirical validations of this theory measure opportunities in terms of geographic locations along one product dimension for the U.S. Cement Industry (Sutton, 1998), the Italian Motor Insurance Industry (Buzzacchi and Valletti, 1999) and in Spanish Retail Banking (de Juan, 2003). In these studies firms tend to have similar market shares within geographical locations. Differences in the aggregate result from firms operating over different numbers of geographical locations. We undertake a similar analysis

<sup>2</sup> Caves (1998) and Sutton (1987) overview the stochastic approach to modelling firm growth.

<sup>3</sup> Introducing a size advantage in the take up of opportunities or allowing for differences in the size of these opportunities (competition within opportunities) will have the effect of introducing greater heterogeneity in firm size and a resulting Lorenz curve that will lie above the lower bound.

for retail Carbonated Soft Drinks. We document the impact of opportunities taken up by firms in terms of geography (store coverage) *and* product segments on market shares in the overall market and within segments. This will give key insights into industry structure and motivates us to investigate how company market share and market power are linked in this industry.

#### A. DATA DESCRIPTION

We use an AC Nielsen panel database of all brands in the Carbonated Soft Drinks Irish retail grocery sector, roughly 12,000 stores. This database provides data on 178 brands, identified for 13 firms and 40 product characteristics, for 28 bi-monthly periods (June/July 1992 to April/May 1997). 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 litres), sales value (thousand pounds), store coverage (based on pure counts of stores, and size weighted by store size in terms of carbonated drinks in which the brand retails to measure effective coverage), forward shelf allocation, firm attachment and product (flavour, packaging, and diet) characteristics.

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 U.S. retail market. Inequality in retail sales as measured by the Gini coefficient is 0.72 in Ireland and 0.68 in the U.S. There are differences between Ireland and the U.S. 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 U.S. Orange and Mixed Fruit are more important segments in Europe. While flavour segments are similar to the U.S., Root Beer and Dr. Pepper type brands never took off in Ireland. In addition, unlike the U.K. retail market for Carbonated Drinks, chain store “own brands” are not a feature of the Irish Market. Like the U.S. it is heavily branded.

#### B. SEGMENTATION OF THE MARKET

An interesting feature of the AC Nielsen data is their identification of various product segments within the market for Carbonated Soft Drinks. They group clusters of brands by forty characteristics: four flavours (Cola, Orange, Lemonade and Mixed Fruit), five different packaging types (Cans, Standard Bottle, 1.5 Litre, 2 Litre and Multi-Pack of Cans) and two different sweeteners (diet and regular). To allow for flavour segments is standard in the analysis of Carbonated Soft Drinks (see Sutton, 1991). Packaging format is recognised as a crucial feature of this market, and exhibit very different seasonal cycles. For example, Cans peak in the summer months of June and July. In contrast, 2 Litre bottle sales peak over the festive months of December and January. Packaging clearly represents different

segments of the market.<sup>4</sup> Thus, we have forty segments delineated in our data as used by A.C. Nielsen in their presentations to companies. As outlined in the next section, our logit models allow for correlations in the error terms for products within a group or segment. A disadvantage often cited is the fact that groups are exogenously specified. Using the same data Walsh and Whelan (2002a) test for segmentation based on the approach taken by Hausman, Leonard and Zona (1994) using Hausman (1978) specification tests to endogenously define or verify that these forty segments are correct.

### C. COVERAGE OF PRODUCT CHARACTERISTICS AND STORES

In Figure 1 we document company coverage of our forty product segments, product coverage of stores based on pure counts of stores, and effective product coverage where the store is weighted by its share of Retail Carbonated Soft Drinks turnover. We undertake 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 store coverage is not company but product specific. For example, Coca-Cola Bottlers clearly has wide distribution with Regular Cola Cans (segment 1). As we move up regular Cola segments by package size, to segments 4 and 5, the number of stores covered declines dramatically, but effective store coverage declines by much less: distribution is targeted at big shops. While these trends are true across other flavours, both regular and diet, we see that distribution is less aggressive in regular Orange and Mixed Fruit segments (6–10 and 15–20). This is where competition from the small companies is greater (see product distribution of all other companies in Figure 1).

In Figure 2 we graph the Sutton (1998) Lorenz curves to see the implications of the product and store configuration in Figure 1 on firm size. We have three Lorenz curves: (1) the actual Carbonated Soft Drink firm size distribution based on output (thousand litres), with an associated Gini coefficient of 0.73; (2) a distribution where size is postulated to be a simple count of product characteristics over which a firm operates (places at least one brand), with a Gini of 0.56; (3) a distribution where size is postulated to be a count of product characteristics, weighted by the percentage of stores that carry this firms product type, yielding a Gini of 0.70. Counts across product characteristics (weighted by store coverage rates) seem to dictate differences in firm market share at the market level.<sup>5</sup> This

<sup>4</sup> Over 90 per cent of cans and standard bottles are impulse buys distributed through small corner stores and garage forecourts rather than chain stores. In contrast, the majority of 2 litre and multi-pack cans are distributed through one-stop supermarket shopping. The 1.5 litre lies somewhere between. The industry has introduced different packaging to satisfy different consumer needs within both the impulse and one-stop shopping segments.

<sup>5</sup> The structure of the market clearly has large companies competing across all segments and facing competition from different small independents within each segment. Each segments market size to sunk cost and the nature of price and non-price competition seems to limit the number of firms

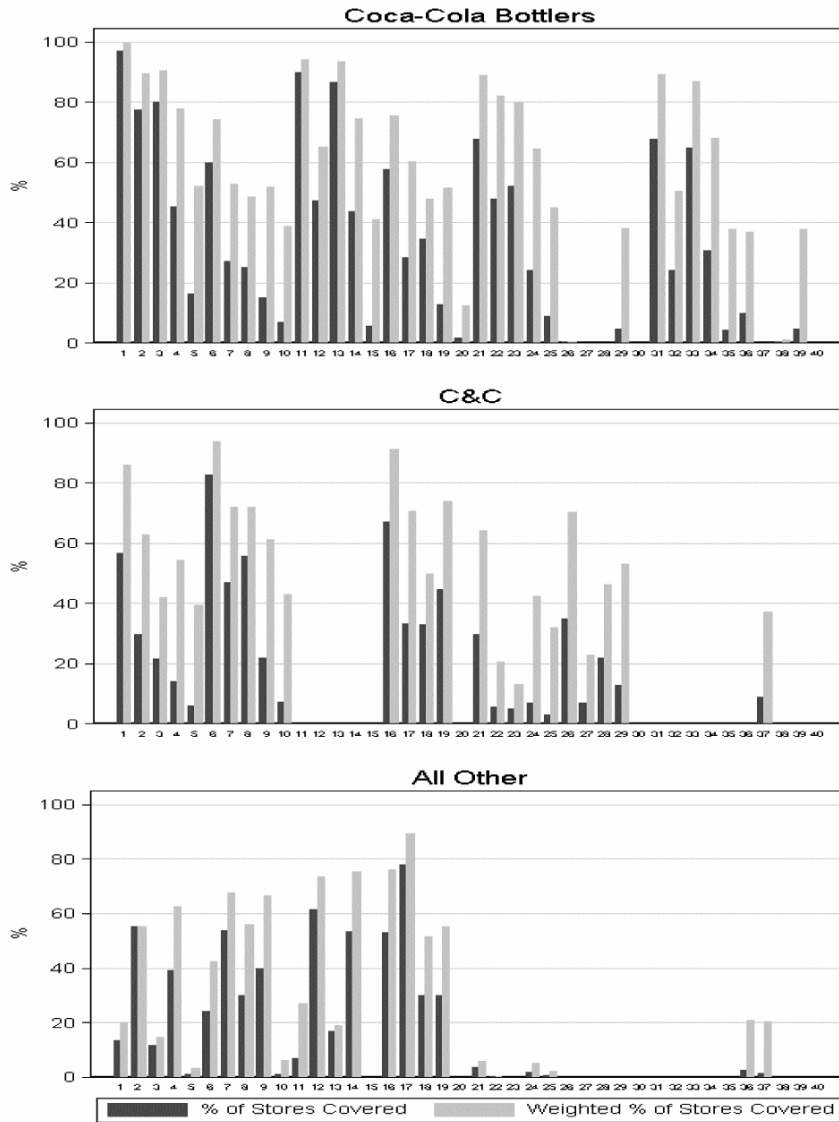


Figure 1. Company Coverage of Stores by Product Segment. Segment numbers represent five packaging types (Cans, Standard, 1.5 Litre, 2 Litre, and Cans Multipacks) for: Regular Cola (1–5); Regular Orange (6–10); Regular Lemonade (11–15); Regular Mixed Fruit (16–20); Diet Cola (21–25); Diet Orange (26–30); Diet Lemonade (31–35) and Diet Mixed Fruit (36–40).

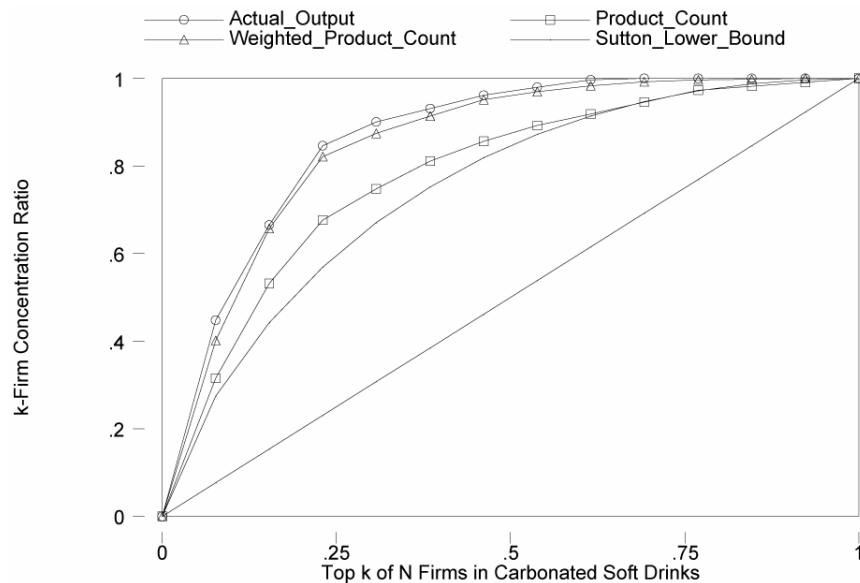


Figure 2. Firm Size Distribution in Carbonated Soft Drinks, Mean 1992–1997.

implies that differences in market shares within segments are small. In Figure 3 we detail and graph an index of specialization, averaged over the period 1992–1997. If a firm sells brands across all product segments and stores the index is zero. As the market shares within product and store segments diverge from that in the overall market, due to specialization in products and stores, the index increases. The index increases dramatically as we move down the firm ranking in overall market share. Small companies have significantly larger market share within their product and location segments. Even though they cover less of the market, they may have localized market power in the product and location space they operate in. This is core issue that we now investigate.

### III. Market Power in Differentiated Goods

In order to evaluate market power when products are differentiated, it is necessary to estimate the degree of substitutability between the various goods in the market. However, a linear demand system for  $n$  brands has  $n^2$  price parameters to estimate. One must therefore place some structure on the estimation.<sup>6</sup>

that can operate with profit (see Walsh and Whelan (2002b)). The numbers of firms that operate in each segment is quite small. Yet, due to certain local taste characteristics, particularly in orange and mixed fruit, small companies can fill a quality window and survive alongside the brands of large companies.

<sup>6</sup> A number of alternative demand specifications have been developed to deal with this dimensionality problem. Representative consumer choice models include the distance metric model (Pinkse, Slade and Brett, 2002), or the multi-stage budgeting model (Hausman, Leonard and Zona, 1994).

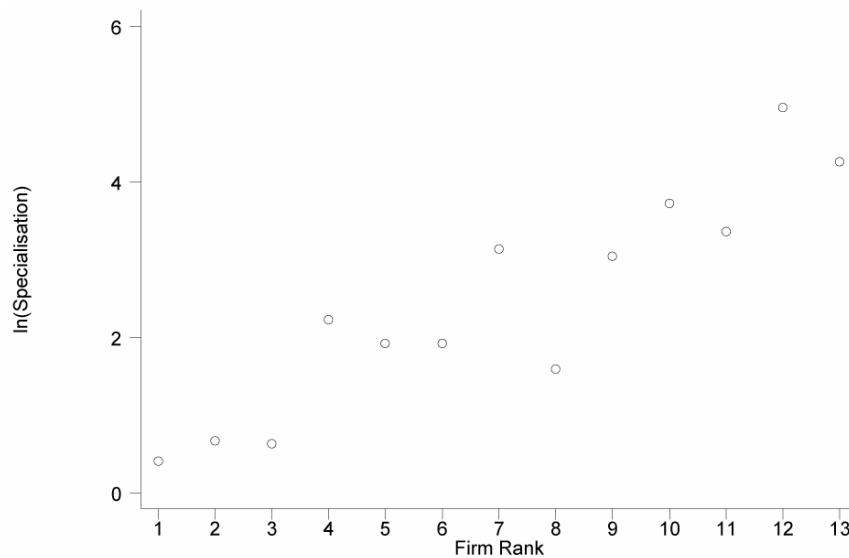


Figure 3. Natural Log of Specialisation of Sales across Product Segments and Stores, Mean 1992–1997. The vertical axis is

$$\ln \text{ Specialisation }_f = \ln \left( \frac{MS_1 + (MS_2 - MS_1) + (MS_3 - MS_1)}{MS_1} \right)$$

where  $MS_1$  denotes firm share of Carbonated Soft Drink sales of the market;  $MS_2$  denotes firm share of Carbonated Soft Drink sales of the product segments in which it sells;  $MS_3$  denotes firm share of Carbonated Soft Drink sales of the stores in which it sells. The index has a lower bound of zero (where a firm sells into all product segments and stores), and increases with the degree of specialisation in products and stores.

In this section we build on the nested logit model of Berry (1994). We augment the demand model by allowing for product  $j$  specific store coverage. A fraction  $D_j$  of consumers face transportation costs or disutility in buying the product  $j$ , while a fraction  $1 - D_j$  have no transportation costs in buying the same product. Our empirical proxy for  $D_j$ , or distance to a product, is one minus the effective product coverage of stores. Rather than just taking the percentage of the 12,000 stores that carry brand  $j$ , we take a weighted sum where each store is weighted by its share of Carbonated Soft Drink sales in the market to get a measure of effective coverage. The greater the effective product coverage of stores, the higher the fraction of consumers that face no transportation costs in buying the product. The property of the nested logit model that leads to *Independence of Irrelevant Alternatives* will be relaxed. Market shares within segments (and in the market) will not be the only source of heterogeneity in primitives of the model (own and cross-price elasticities). Brand  $j$  specific differences in store coverage will also drive primitives.

Discrete choice models include the vertical model (Bresnahan, 1987), the logit or nested logit models (Berry, 1994) or a random coefficient model (Berry, Levinsohn and Pakes, 1995).

The nested logit model has a demand equation that is based on a random-utility model in which an individual consumes one unit of the product that yields the highest utility, where products include the outside good. As opposed to the ordinary logit model, the  $n$  brands or products are partitioned into  $G + 1$  groups,  $g = 0, 1, \dots, G$ , with the outside good  $j$  the only one present in group 0. It allows for correlations in the error terms for products within defined groups. We define the utility of consumer  $i$  for product  $j$  that face no transportation costs and for consumer  $k$  that face a transportation cost  $t$ , respectively as,

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \zeta_{ig} + (1 - \sigma)\varepsilon_{ij} \quad (2)$$

$$u_{kj} = x_j\beta - \alpha_l(p_j + t) + \xi_j + \zeta_{kg} + (1 - \sigma)\varepsilon_{kj}$$

where  $x_j$  is a vector of observed characteristics of product  $j$ ;  $p_j$  is the price of product  $j$  (we allow for a different response from the two consumer groups) and  $t$  is a per unit disutility; and  $\xi_j$  is a vector of product characteristics unobserved to the econometrician. The variation in consumer tastes enters only through the terms  $\zeta_{ig} = \zeta_{kg}$ ,  $\varepsilon_{ij}$  and  $\varepsilon_{kj}$ . Note that  $\varepsilon_{ij}$  and  $\varepsilon_{kj}$  are specific to product  $j$ , which is assumed to be an identically and independently distributed extreme value. For consumers,  $\zeta_{ig}$  is utility common to all products within a group  $g$  and has a distribution function that depends on  $\sigma$ , with  $0 \leq \sigma < 1$ . As the parameter  $\sigma$  approaches one, the within group correlation of utility levels across products goes to one (products within groups are perfect substitutes). As  $\sigma$  tends to zero, so too does the within group correlation.<sup>7</sup> We aggregate over the fraction  $1 - D_j$  of consumers  $i$ , and aggregate over the fraction  $D_j$  of consumers  $k$  to define the unknown parameter vector  $\delta$  (describing the mean utility level of a product)<sup>8</sup>

$$\delta_j = x_j\beta - \alpha p_j + (\alpha - \alpha_1) \ln(D_j)p_j - \beta_1 \ln(D_j) + \xi_j \quad (3)$$

As shown in Berry (1994), from Equation (3) we can derive the product market shares which depend upon the mean utility level of a product, and we can treat these mean utility levels as known non-linear transformations of market shares such that  $\delta_j$  can be written as the following linear demand equation:

$$\begin{aligned} \ln(s_j) - \ln(s_0) = & x_j\beta - \alpha p_j + (\alpha - \alpha_1) \ln(D_j)p_j - \beta_1 \ln(D_j) \\ & + \sigma \ln(s_{jg}) + \xi_j \end{aligned} \quad (4)$$

where  $s_j$  is product  $j$ 's (the brand) share of the entire market (inside plus outside goods total). We define the entire market, the sum of carbonated sales over all

<sup>7</sup> When  $\sigma = 0$  this reduces to the ordinary logit model, where substitution possibilities are completely symmetric, for example as when all products belong to the same group.

<sup>8</sup> We use  $\ln(D_j)$  in our econometric work. The fraction of the consumer populations with transportation costs will thus be  $\ln(D_j)/(\ln(D_j) - (1 - \ln(D_j)))$  and without transportation costs will be  $1 - (\ln(D_j)/(\ln(D_j) - (1 - \ln(D_j))))$ .



brands (inside goods) plus potential sales (outside good), as 330 ml carbonates per day for the population of Ireland.<sup>9</sup> The outside goods' share of the entire market is  $s_0$ , and  $x_j$  is a vector of observed characteristics of product  $j$ : *Flavour*, *Packaging*, *Sweetener*, *Season*, *Packaging*  $\times$  *Season*, and *Firm Ownership* dummies. Sales by Packaging have different peak seasons, which the interaction term allows for. The variable  $D_j$  is the distance to a product  $j$ , as previously defined.  $p_j$  is the product price per litre deflated by the weighted (brand market share) average price of all brands in Carbonated Soft Drinks normalised to 1 in the first year.  $\ln(D_j)p_j$  augments the price effect by our distance measure per product.  $s_{jg}$  is  $j$ 's segment share of the group  $g$  to which it belongs, and  $\xi_j$  is an unobserved (to the econometrician) product characteristic that is assumed to be mean independent of  $x_j$ . We need estimates of  $\alpha_j = \alpha + (\alpha - \alpha_1) \ln(D_j)$  and  $\sigma$  to get our corresponding nested logit own-price and cross-price elasticities outlined in Equations (5) and (6), respectively,

$$\varepsilon_{jj} = \alpha_j p_j \left[ s_j - \frac{1}{(1-\sigma)} + \frac{\sigma}{(1-\sigma)} s_{jg} \right] \quad (5)$$

$$\varepsilon_{jk} = \begin{cases} \alpha_k p_k \left[ s_k + \frac{\sigma}{(1-\sigma)} s_{jg} \right] & \text{if } k \neq j \text{ and } k \in g \\ \alpha_k p_k s_k & \text{if } k \neq j \text{ and } k \notin g \end{cases} \quad (6)$$

It is important to note that the elasticities here refer to the percentage change in market share in response to a change in  $p_j$ . Estimates of  $\alpha_j$  and  $\sigma$  from Equation (4) are obtained using instrumental variables since the product price and the within group share are endogenous variables and must be instrumented. Our identification strategy has some innovations.

#### A. INSTRUMENTS

Our identification strategy is to use Hausman and Taylor (1981) and BLP (Berry, Levinsohn and Pakes) (1995) type instruments. Hausman and Taylor (1981) and Hausman, Leonard and Zona (1994) assume systematic cost factors are common across segments and short-run shocks are not correlated with those factors. 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 disturbances in the product demand equations and can be used as an instrument. We use an over-identifying restriction test to see whether the moments (instruments) conditions are independent of the error structure.

We also use non-price Hausman and Taylor (1981) instruments, where the average effective coverage of stores and forward shelving allocations by firms brands

<sup>9</sup> This is a reasonable approximation. It should be noted that the largest bi-monthly carbonated sales in our data is equivalent to each person in Ireland consuming 220 ml per day.

in *other* segments are instruments in a defined segment, again allowing for firm and segment fixed effects. This captures cost gains from economies of scope in retail distribution by a company carrying portfolios of brands across segments.

In addition, we use within segment BLP (1995) type instruments: the average effective coverage of stores by other firms and the average shelf-space in terms of forward stock allocation given to other firms in retail stores *within* the segment of the brand. The idea here is that distribution structures of other brands (whether you are in stores and shelf-space allocation within stores) are pre-determined longer-term outcomes that influence the intensity of short-run price competition that a brand faces in a segment.

A final instrument that we use is the average deflated price of brands belonging to other firms within a segment in the initial period. It is clear from Table IV that the average price per litre varies by segment, in particular by packaging type. This clearly reflects equilibrium price discrimination that persists. Cans are always a factor of 2.5 times higher than 2-litre containers. Cans are mainly sold in small shops as impulse buys, and there is an equilibrium premium that consumers pay for convenience. On the other hand 2-Litre containers mainly sell in chain stores (supermarkets) and do not extract any convenience premium. The instrument is a weighted packaging by flavour by diet fixed effect. We test whether the cross-section equilibrium price discrimination effect is a valid instrument.

## B. THE SUPPLY SIDE

Having valid instruments we intend to estimate  $\alpha_j$  and  $\sigma$  to define the demand side primitives, by product, outlined in Equations (5) and (6). Using these demand side primitives, via an equilibrium pricing system of equations, to be defined, we can back out the price cost markup (Lerner Index) for each brand. Firms maximise the sum of profits accruing from their brands,  $f_j$ . In brand price setting,  $p_b$ , a firm takes the price of all other firms' brands as given. The firm internalises the cross-price effect on market share of the brands it owns in the price setting of an individual brand. The first order condition for each brand will have the general form,

$$s_j + \sum_{b \in f_j} (P_j - c_j) \frac{\partial s_j}{\partial P_b} = 0 \quad b, j \in f_j \quad (7)$$

Given marginal costs  $c_j$ , a multi-product Nash equilibrium is given by the system of  $J$  first order conditions.<sup>10</sup> Using our primitives, around 154<sup>2</sup> in each period,

<sup>10</sup> We assume that retailers, distributors and manufacturers act in their joint interest. In this highly branded market it is very difficult for retailers and distributors to go against recommended retail prices set by the manufacturers. Even in small stores Carbonated Soft Drinks are traffic builders for other items. Walsh and Whelan (1999) document that price dispersion in Carbonated Soft Drinks Cans across independent (small) stores is low relative to other food and drink products. Stores do not seem to go against recommended retail prices set by the manufacturers.

the first order condition for the nested logit implies product price equals marginal cost plus a markup.<sup>11</sup> Given the primitives of the demand system we will be able to calculate a markup for each brand. Even though we impose no structure on marginal cost, the primitives are likely to be estimated with error so we will back out a markup with errors. We will allow for this error in our second step estimation on the factors that drive the estimated markup.

### C. RESULTS OF NESTED LOGIT MODEL

We estimate the demand system in Equation (4). Estimates of the vector  $\beta$ ,  $\beta_1$ ,  $\alpha$ ,  $\alpha_1$ , and  $\sigma$  can be obtained from a GMM estimation procedure. The variables  $p_j$ ,  $\ln(D_j)p_j$  and  $\ln(s_{jg})$  are endogenous variables and must be instrumented. Our identification strategy (instruments) is outlined above.

Our results are presented in Table I. In column I we present a nested logit model without an interaction term between price and distance. In column II we estimate the model in Equation (4). In both specifications, the  $\chi^2$  test rejects the null that the moments (instruments) are invalid. We estimate a  $\sigma = 0.70$  in column II. For our corresponding nested logit own-price and cross-price elasticities, this will imply that within segment market shares will get a higher weight than the overall market share. In addition we see that  $\alpha_j = -2.9 + 0.5 \ln(D_j)$ . This will give us a matrix of nested logit own-price and cross-price elasticities outlined in Equations (5) and (6), respectively. In Table II, we document a sample of these for brand averages in litre bottle regular segments, for the last period. The nested logit Model with the interaction term gives us more sensible primitives. We see some variation in the own-price elasticity. The cross-price elasticity, on average, coming from all brands in other segments is small. Yet, the within segment cross-price elasticity, on average, is important and has lots of variation. Given these primitives, assuming multi-product price setting firms without symmetry in the market, a multi-product Nash equilibrium is given by the system of  $J$  first order conditions. Using the first order condition in Equation (7) for the nested logit implies that we can get estimates of a Lerner Index per brand  $j$ .

### D. SECOND STEP MODEL OF ESTIMATED BRAND MARKUPS

In Table III we document firm's markups by market share in the overall market (Inside and Outside). We aggregate over a firm's brands by taking a strict average, median outcome and a weighted average (weighted by a brand share of company sales). The descriptive statistics on company market power estimates seem to indicate that market power does not vary systematically with company size. In Table IV we average over all brands within each segment to show the variation in the

<sup>11</sup> We assume that a Nash equilibrium exists. Caplin and Nalebuff (1991) prove existence for a general discrete choice model, assuming single product firms. Anderson and de Palma (1992) prove existence for the nested logit model with multiproduct firms, assuming symmetry.

Table I. GMM estimation of the reduced form demand function

Dependent variable: $\ln(S_j) - \ln(S_0)$	Regression I		Regression II	
	Coefficient	(t-stat)	Coefficient	(t-stat)
Constant	-3.1	(8.1)*	-3.7	(10.1)*
Default Cola				
Orange	0.9	(14.9)*	0.7	(10.3)*
Lemonade	0.01	(0.1)	-0.01	(0.2)
Mixed Fruit	0.23	(3.8)*	0.06	(1.1)
Default Cans				
Standard	2.04	(11.6)*	1.6	(9.1)*
1.5 Litre	2.3	(12.1)*	1.8	(9.4)*
2 Litre	0.29	(1.8)	0.07	(0.4)
Multi-Pack Cans	1.1	(5.4)*	0.9	(4.5)*
Default Regular				
Diet	1.9	(18.5)*	1.6	(7.2)*
$-\beta_1 \ln(D_{jt})$	0.12	(8.4)*	0.94	(6.7)*
$\sigma \ln(s_{gjt})^a$	0.91	(23.1)*	0.70	(9.5)*
$(\sigma - \alpha_1) \ln(D_{jt})p_{jt}^a$			0.48	(5.7)*
$-\alpha p_{jt}^a$	3.4	(9.1)*	2.9	(7.9)*
Company Dummies	Yes		Yes	
Packaging $\times$ Season Dummies	Yes		Yes	
$R^2$	0.72		0.81	
Numbers of Observations	4,645		4,645	
Over-identification IV Test	$\chi^2(5) = 0.99$		$\chi^2(5) = 0.99$	

<sup>a</sup>Instruments for Regression I include all the regressors, with the exception of  $p_{jt}$  and  $\ln(s_{gjt})$ ; *Forward Shelving* $_{jt}$ ; Hausman-Taylor instrumental variables (brands of the same firm in other segments) with respect to  $p_{jt}$ ,  $\ln(D_{jt})$ , and *Forward Shelving* $_{jt}$ ; and BLP instruments (brands of the other firms in the same segment) with respect to  $\ln(D_{jt})$ , *Forward Shelving* $_{jt}$  and initial period  $P_{jt}$ . Instruments for Regression II include all instruments used for Regression I with the addition of  $\ln(D_{jt})p_{jt}$  and Hausman-Taylor instrumental variables with respect to  $\ln(D_{jt})p_{jt}$ . \*Significantly different from zero at the five percent level in a two-tailed test.

estimated markups across segments. We see that the markup varies by packaging. In particular, 1.5 and 2-litre bottles have greater markups than cans and the standard bottle. Diet drinks seem to also get a premium, while Lemonade seems to have higher markups compared to other flavours.

In Table V we estimate a reduced form relationship between our estimates of brand market power and company dummies, listed by their rank in terms of its market share, controlling for product characteristics, an error correction term (absolute deviation of the residual for brand  $j$  from the mean, taken from our demand model) and controls for seasonal cycles by packaging type. Company attachment,

Table II. Sample of estimated own and cross-price brand elasticities in May 1997

Segment	Average own price elasticity	Average within cross price elasticity	Average between cross price elasticity
<i>Cola Regular Litre Bottle</i>			
Nested Logit	-16.68	5.08	0.17
Nested Logit with interaction	-6.82	2.03	0.06
<i>Orange Regular Litre Bottle</i>			
Nested Logit	-18.39	3.73	0.17
Nested Logit with interaction	-6.84	1.37	0.06
<i>Lemonade Regular Litre Bottle</i>			
Nested Logit	-14.93	3.45	0.17
Nested Logit with interaction	-6.58	1.89	0.07
<i>Mixed Fruit Regular Litre Bottle</i>			
Nested Logit	-19.31	2.74	0.16
Nested Logit with interaction	-7.48	1.09	0.06

Table III. Company markups: Various aggregation over brands 1992-1997

Companies	Brands	Market share %	Mean	Median	Weighted Mean
Rank 1	52	25.5	0.14	0.13	0.19
Rank 2	45	20.0	0.15	0.14	0.14
Rank 3	20	5.9	0.20	0.18	0.27
Rank 4	5	3.2	0.16	0.11	0.29
Rank 5	5	3.0	0.26	0.31	0.31
Rank 6	7	2.1	0.12	0.11	0.16
Rank 7	4	1.7	0.06	0.06	0.05
Rank 8	7	1.2	0.12	0.11	0.14
Rank 9	6	0.1	0.16	0.12	0.15
Rank 10	1	0.02	0.10	0.10	0.10
Rank 11	2	0.01	0.09	0.08	0.08
Rank 12	1	0.01	0.09	0.09	0.09
Rank 13	1	0.01	0.07	0.07	0.07

Table IV. Segment (averages) over brands 1992-1997

Segment	Brands	Firms	Markup	Price per Litre
Cola Regular Cans	6	5	0.08	1.30
Cola Regular Standard	11	5	0.08	1.47
Cola Regular 1.5 Litre	3	3	0.16	0.67
Cola Regular 2 Litre	5	4	0.21	0.49
Cola Regular Cans Multipacks	5	2	0.14	0.98
Orange Regular Cans	6	4	0.08	1.34
Orange Regular Standard	10	6	0.08	1.44
Orange Regular 1.5 Litre	5	4	0.15	0.70
Orange Regular 2 Litre	5	4	0.20	0.52
Orange Regular Cans Multipacks	3	3	0.12	1.03
Lemonade Regular Cans	4	2	0.11	1.16
Lemonade Regular Standard	5	2	0.11	1.32
Lemonade Regular 1.5 Litre	3	2	0.20	0.60
Lemonade Regular 2 Litre	4	2	0.29	0.46
Lemonade Regular Cans Multipacks	2	1	0.19	0.97
Mixed Fruit Regular Cans	7	5	0.07	1.39
Mixed Fruit Regular Standard	19	10	0.08	1.26
Mixed Fruit Regular 1.5 Litre	7	6	0.17	0.75
Mixed Fruit Regular 2 Litre	8	6	0.23	0.48
Mixed Fruit Regular Cans Multipacks	1	1	0.15	0.83
Cola Diet Cans	4	3	0.10	1.28
Cola Diet Standard	3	3	0.08	1.27
Cola Diet 1.5 Litre	4	2	0.17	0.75
Cola Diet 2 Litre	4	3	0.25	0.54
Cola Diet Cans Multipacks	3	2	0.13	1.05
Orange Diet Cans	2	2	0.12	1.25
Orange Diet Standard	1	1	0.10	1.19
Orange Diet 1.5 Litre	1	1	0.15	0.71
Orange Diet 2 Litre	3	1	0.19	0.56
Lemonade Diet Cans	2	2	0.11	1.40
Lemonade Diet Standard	1	1	0.08	1.29
Lemonade Diet 1.5 Litre	1	1	0.20	0.71
Lemonade Diet 2 Litre	2	1	0.29	0.57
Lemonade Diet Cans Multipacks	1	1	0.18	0.96
Mixed Fruit Diet Cans	2	2	0.09	1.24
Mixed Fruit Diet Standard	2	2	0.09	1.15
Mixed Fruit Diet 2 Litre	1	1	0.14	0.83

Table V. Second step model of brand market power

Dependent variable: Natural log of estimated markup clustered by segments		
	Coefficient	(t-stat)
Default Cola		
Orange	-0.04	(0.9)
Lemonade	-0.03	(0.8)
Mixed Fruit	0.04	(0.8)
Default Cans		
Standard	-0.03	(0.3)
1.5 Litre	0.65	(8.6)*
2 Litre	0.99	(9.8)*
Multi-Pack Cans	0.48	(5.8)*
Default Diet		
Regular	-0.14	(3.4)*
Default Rank 1		
Rank 2	-0.01	(0.1)
Rank 3	0.37	(4.3)*
Rank 4	0.28	(4.2)*
Rank 5	0.53	(4.1)*
Rank 6	-0.03	(0.6)
Rank 7	-0.55	(1.4)
Rank 8	-0.12	(1.2)
Rank 9	-0.02	(0.5)
Rank 10	0.02	(0.4)
Rank 11	-0.14	(2.2)*
Rank 12	0.04	(1.1)
Rank 13	-0.33	(7.1)*
Demand Error Correction	-0.69	(3.7)*
Constant	-2.3	(8.8)*
<i>Packaging × Season Dummies</i>	Yes	
$R^2$	0.79	
Numbers of Observations	4,645	

\*Significantly different from zero at the five percent level in a two-tailed test.

relative to the default top company, reduces brand markups in two cases, makes no difference in seven cases and we observe higher markups in three cases. Brands in larger packaging and diet characteristics seem to extract a higher premium. The product characteristics of a brand are more important for rent extraction than company attachment. Brands belonging to the top two multinationals do not sys-

tematic extract more rent than brands belonging to the small Irish/British owned companies.

#### IV. Conclusions

The Sutton (1998) approach shows us that the heterogeneous placing of brands *across* product and location space in Carbonated Soft Drinks is the main determinant of dispersion in market share. We investigated whether the lack of heterogeneity in market shares *within* these dimensions has harmonised company markups using a structural model. Our analysis shows that production differentiation by location, in addition to product characteristics, is an important determinant of brand markups. Clearly smaller companies, within the product segments and stores of the market they operate in, extract rents comparable to multinationals that operate across most stores and product segments. It seems that inferring market power from the distribution of market shares is ill advised in multi-product firms differentiated goods industries.

#### Acknowledgements

This paper was presented at the IIOC Conference in Boston 2003, Harvard University IO group, Wesleyan College and University of Venice. We thank John Asker, Agar Brugiavini, Julie Mortimer, Ariel Pakes, and seminar participants for helpful comments. We are also grateful for excellent comments from Christopher Snyder and an anonymous referee.

#### References

- Anderson, Simon P., and Andre de Palma (1992) 'Multiproduct Firms: A Nested Logit Approach', *Journal of Industrial Economics*, **60**, 261–276.
- Berry, Steven (1994) 'Estimating Discrete-Choice Models of Product Differentiation', *RAND Journal of Economics*, **25**, 242–262.
- Berry, Steven, James Levinsohn, and Ariel Pakes (1995) 'Automobile Prices in Market Equilibrium', *Econometrica*, **63**, 841–890.
- Bresnahan, Timothy (1982) 'The Oligopoly Solution Concept is Identified', *Economic Letters*, **10**, 87–92.
- Bresnahan, Timothy (1987) 'Competition and Collusion in the American Automobile Industry: The 1955 Price War', *Journal of Industrial Economics*, **35**, 457–482.
- Bresnahan, Timothy (1989) 'Empirical Methods for Industries with Market Power', in Richard Schmalensee and Robert D. Willig, eds., *Handbook of Industrial Organization*, Vol. 2. New York: North-Holland, pp. 1011–1057.
- Buzzacchi, Luigi, and Tommaso Valetti (1999) 'Firm Size Distribution: Testing the Independent Submarkets Model in the Italian Motor Insurance Industry', Discussion Papers Series EI, STICERD, LSE.
- Caplin, Andrew, and Barry Nalebuff (1991) 'Aggregation and Imperfect Competition: On the Existence of Equilibrium', *Econometrica*, **59**, 25–60.



- Caves, Richard E. (1998) 'Industrial Organization and New Findings on Turnover and Mobility of Firms', *Journal of Economic Literature*, **36**, 1947–1982.
- de Juan, Rebecca (2003) 'The Independent Submarkets Model: An Application to the Spanish Retail Banking Market', *International Journal of Industrial Organization*, **21**, 1461–1488.
- Genesove, David, and Wallace P. Mullin (1998) 'Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry', *RAND Journal of Economics*, **29**, 355–377.
- Hausman, Jerry (1978) 'Specification Tests in Econometrics', *Econometrica*, **46**, 1251–1272.
- Hausman, Jerry and W. Taylor (1981) 'Panel and Unobservable Individual Effects', *Econometrica*, **49**, 1377–1398.
- Hausman, Jerry, Gregory Leonard, and J. Douglas Zona (1994) 'Competitive Analysis with Differentiated Products', *Annales D'Economie et de Statistique*, **34**, 159–80.
- Pinkse, Joris, Margaret E. Slade, and Craig Brett (2002) 'Spatial Price Competition: A Semi-parametric Approach', *Econometrica*, **70**, 1111–1155.
- Sutton, John (1991) *Sunk Costs and Market Structure: Price Competition, Advertising and the Evolution of Concentration*. Cambridge, MA: MIT Press.
- Sutton, John (1997) 'Gibrat's Legacy', *Journal of Economic Literature*, **35**, 40–59.
- Sutton, John (1998) *Technology and Market Structure*. Cambridge, MA: MIT Press.
- Walsh, Patrick P., and Ciara Whelan (1999) 'Modelling Price Dispersion as an Outcome of Competition in the Irish Grocery Market', *Journal of Industrial Economics*, **47**, 1–19.
- Walsh, Patrick P., and Ciara Whelan (2002a) 'Product Differentiation and Firm Size Distribution: An Application to Carbonated Soft Drinks', Discussion Papers Series EI/31, STICERD, LSE.
- Walsh, Patrick P., and Ciara Whelan (2002b) 'Portfolio Effects and Firm Size Distribution: Carbonated Soft Drinks', *The Economic and Social Review*, **33**, 43–54.

