Merger Control in Differentiated Product Industries*

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May 15, 2005

Abstract

Thresholds defined on the level and change in the HHI (Herfindahl-Hirschmann Index) applied to market shares seem to be the main instrument to select notified mergers for investigation in both the EU and US. We question the use of such a selection rule in differentiated products industries. We propose the use of a structural approach to apply HHI thresholds based on profit shares rather than market shares. We illustrate our point using product data for Retail Carbonated Soft Drinks (Price, Market Share and Characteristics). We estimate company (product) mark-ups consistent with a structural model of equilibrium, using demand primitives from a Nested Logit model and a Random Coefficient model. We provide an example where the HHI thresholds based on profit shares identify potentially damaging mergers not captured by applying thresholds to output shares, or conversely, identify mergers of no concern that would be selected on the basis of output shares.

Keywords: Market Shares, Market Power, Differentiated Products Industries, Merger Screening.

JEL classifiers: K2, L11, L25, L40, L81.

*This paper was written for CESifo's Venice Summer Institute 2004, "Recent Developments in Antitrust Analysis", 21-22 July 2004. We thank our discussant Vivek Ghosal for useful comments. We also acknowledge comments from the Competition and Regulation Group, Dublin. We also thank Peter Davis, Gautam Gowrisankaran, Julie Mortimer, Ariel Pakes and John Sutton for comments on work that this policy paper is based on.

1 Introduction

The recent EU Merger Control Regulation No 139/2004 has, with few notable exceptions, adopted an analytical framework that is similar to the US Horizontal Merger Guidelines. Under Article 2 of EU legislation, any merger that will *"significantly impede effective competition in the common market or in a substantial part of it"* should be blocked.[1] This moves the EU criteria closer to the US practice, where mergers are prohibited if they would result in a *"substantial lessening of competition"*. While this move away from "*dominance*" may be apparent during the investigation of mergers, an analysis of market concentration is still at the centre of the selection stage of all notified mergers in the EU and US.

In both the EU and US Merger Guidelines, thresholds have been defined based on the level and changes in the Herfindahl-Hirschmann Index (HHI) to provide a screening rule on whether or not proposed mergers justify investigation (outlined in Table 1).[2] Even though the thresholds are not ex-ante the sole criteria to select notified mergers for further investigation, an ex-post examination of concentration data and mergers challenged reveals that levels and changes in the HHI are at the centre of the selection process. This evidence is documented in section 2.

Rather than screening on the basis of market share, we propose the use of a structural approach in differentiated products industries to estimate and assess changes in market power that arise from mergers of undertakings. This approach only requires company product data on prices, market shares and product characteristics. Using an industry study, which we describe in section 3, we outline a structural methodology to estimate company mark-ups consistent within a structural model of equilibrium using Berry (1994). Demand primitives are estimated using a Nested Logit model of demand and used to back out price cost mark-ups from a model of company multi-product Nash pricing. We also outline a comparable, though more sophisticated, model to estimate company mark-ups using the Berry, Levinsohn and Pakes (1995) (henceforth, BLP). In this case demand primitives are estimated using a Random Coefficient model of demand incorporating data on consumer demographics and price-cost mark-ups are estimated jointly with demand consistent with a structural model of multi-product Nash pricing. Our theoretical framework is outlined in section 4.

We compare our estimates of demand primitives and price cost mark-ups from both of these procedures in section 5. The policy recommendation we propose is that thresholds based on the level and changes in the HHI that select notified mergers for further investigation should be applied to profit shares in differentiated products industries (rather than market shares).[3] Using our results we provide an example of a hypothetical merger in undertakings with limited combined market share that can result in a substantial increase in market power. In addition, we provide an example whereby a hypothetical merger in undertakings with very large combined market share can result in a small increase in market power. We argue that existing selection rules based on dominance may not only overlook damaging mergers but may select mergers for investigation that have little competitive concern. Over the period 1990 - 2004, of the 2,400 EU mergers notified, only 144 cases where selected for investigation. Most cases were allowed to process subject to undertakings and some withdrew. Only 18 cases were blocked (see European Commission, 2004).[4] Given the low selection rates in the EU and US, the success of merger control depends heavily on the selection criteria. We feel structural models should be used to estimate profit shares during screening to ensure selected mergers are more likely to be damaging and hence blocked. We conclude in section 6.

2 Merger Regulations and the Role of Concentration in Merger Screening

Under Article 2 of EU Merger Control Regulation No 139/2004, merger control moves the EU criteria closer to the US practice.[5] Thus, mergers are assessed as to whether or not they enhance the market power of companies and, subsequently, are likely to have adverse effects for consumers in the form of higher prices, poorer quality products, or reduced choice.[6] The EU Merger Guidelines (2004/C 31/03) outline two ways that horizontal mergers may impede effective competition: (i) by eliminating important competitive constraints on one or more firms, which consequently would have increased market power, without resorting to coordinated behavior (non-coordinated or unilateral effects)[7], and (ii) by changing the nature of competition that raises prospects for coordination (coordination effects) i.e. merger results in collective dominance.[8] This is similar to the US Horizontal Merger Guidelines. Any full assessment of a merger would also examine the existence of any possible countervailing forces to market power, such as countervailing buyer power, possibility of entry which would maintain effective competition, efficiencies arising from the proposed merger, or conditions for the failing firm defence.

Yet, before these considerations are implemented during investigation, a preliminary screening of all notified mergers takes place in order to decide which mergers justify a full investigation. Both EU and US guidelines still use market shares and concentration levels as first indications of the competitive importance of both the merging parties.[9] Section III of the EU Merger Guidelines outlines specific market share and concentration levels where the Commission is likely to have, or not, competitive concerns.[10] EU guidelines apply a HHI and change in the HHI as a result of a proposed merger to provide a first indication of the change in competitive pressure following a merger. *"Non-interventionist"* thresholds are documented in Table 1. Except in special circumstances, detailed below, the Commission is unlikely to identify horizontal competition concerns in a market with post merger HHI below 1000; in a market with a post-merger HHI between 1000 and 2000 with an increase in the HHI of less than 250; or in a market with a post-merger HHI greater than 2000 with an increase in the HHI of less than 150. Proposed mergers in these categories, it is said, do not normally require extensive analysis. The screening thresholds outlined in the US Horizontal Merger Guidelines are slightly different, more strict, than the EU and are outlined in Table 1. Once again, ordinarily no further analysis is required for those proposed mergers yielding a post-merger HHI of less than 1000; a post-merger HHI between 1000 and 1800 with an increase in the HHI of less than 100; or a post-merger HHI greater than 1800 with an increase in the HHI of less than 50. For those mergers that break the thresholds, a full investigation is justified.

The HHI and change in the HHI on market shares are not supposed to be the only criteria that selection is based on. Special circumstances can lead to selection:.if a merger involves a potential entrant or a recent entrant with a small market share; if one or more parties are important innovators that is not reflected in market share; if there are significant cross-shareholdings among the market participants; if one of the merging firms is a maverick firm with a high likelihood of disrupting coordinated conduct; if indications of past or ongoing coordination, or facilitating practices, are present; if one of the merging parties has a pre-merger market share of 50% or more. According to well established case law, very large market shares (50% or more) may in themselves be evidence of the existence of a dominant market position.[11] However, other factors like the strength and number of competitors, presence of capacity constraints or the extent to which the products of the merging firms are close substitutes may be important.[12]

Verouden (2004) refers to a Commission analysis relating HHI and change in the HHI (delta) to large number of past decisions.[13] Although at first glance there appeared to be little evidence of a relationship between levels and changes in HHI and those cases in which the Commission is not likely to have competitive concerns, *"a further analysis, of those cases where the Commission identified competition concerns, but where either the HHI or the delta were not particularly high, revealed that typically one or several special circumstances could be identified that made the particular estimate for the market share, and consequently, the HHI and the delta not very informative"* (Verouden, 2004, pg.6).[14] Allowing for these *"special circumstances"*, thresholds are clearly reflected in past cases.

The US Federal Trade Commission and DOJ (2003) examined concentration data and the numbers of mergers challenged for Fiscal Years 1999 - 2003. Table 2 relates post-merger HHI and change in the HHI associated with decisions to challenge mergers (either in court or administratively) over this period.[15] The data relate to 173 mergers covering 1263 relevant markets. The lowest HHI recorded just slightly exceeded 1400. Thus, no proposed merger with a post-merger HHI of < 1000 was challenged over the period examined. The lowest value for the change in HHI is approximately 85. Thus, no merger resulting in a delta of < 85 (irrespective of post-merger concentration levels) were challenged. From the table we see that there does not appear to be a violation of the "*non-*

interventionist" thresholds set out in the US Horizontal Merger Guidelines. Moreover, we observe that the number of mergers challenged tends to be higher the more (post-merger) concentrated the industry, and/or the higher the change in concentration that results from the merger.

It therefore appears that market share and concentration analysis play an important role in the initial screening stage of mergers. In what follows, we question the relevance of this for differentiated products industries. Rather than screening on the basis of market share, we propose the use of a structural approach in differentiated products industries to assess changes in profit shares that arise from mergers of undertakings. This will result in a set of mergers being investigated that could be very different to that selected under market share assessment.

3 Industry and Data

AC Nielsen, an international marketing research company, has collated a panel database of all brands in Carbonated Soft Drinks distributed throughout all 12,000 Irish retail stores for use in empirical analysis. The database provides bi-monthly population data spanning October 1992 to March 1997 for 178 brands, identified for 13 firms and 40 product characteristics within the particular *"business"* of 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. The evolution of the Irish grocery market from the early 1970s to its present day structure is described in Walsh and Whelan (1999) and the data used in this paper is outlined further in Mariuzzo, Walsh and Whelan (2003).

We have brand level information on the per litre brand price (weighted average of brand unit prices across all stores selling the brand, weighted by brand sales share within the store), quantity (thousand liters), 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), inventories (number of days to stock out on day of audit given the current rate of purchases), firm attachment and product (flavor, packaging, diet) characteristics.

An interesting feature of the AC Nielsen data is their identification of various product characteristics 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 (Cans, Standard Bottle, 1.5 Litre, 2 Litre and Multi-Pack of Cans) and 2 different sweeteners (Diet and Regular). The number and size of the product characteristics was very stable throughout the period of this study. To allow for flavor segments is standard in the analysis of Carbonated Soft Drinks [see Sutton (1991)]. Packaging format is also a crucial feature of this market. First, packaging format controls for different seasonal cycles, Cans peak in the summer months of June and July and 2 Litre bottles sales peak over the winter months of December and January. Secondly, 90 per cent of Cans and Standard bottles are distributed through small stores rather than chain stores. In contrast, the majority of 2 Litre and Multi-Pack cans are distributed through chain stores. Packaging also controls for the nature of the buy: impulse versus one-stop shopping; small versus large store.

Another feature of the data is that companies coverage of the 40 product segments of the market with brands is very different (see Mariuzzo, Walsh and Whelan (2003)) In addition, brand coverage of stores within segments based on effective coverage of stores, where the store is weighted by its share of Retail Carbonated Soft Drinks turnover, is also very brand specific. The top two companies, Coca-Cola Bottlers and C&C (Pepsico franchise), have broad coverage of the product segments. Yet, brand coverage of stores is not company but product specific. For example, Coca-Cola Bottlers has wide distribution with Regular Cola Cans, while the distribution is less aggressive in regular Orange and Mixed Fruit characteristics. This is where competition from the small companies (Irish/British) is greater. The important point for our econometric analysis is that (effective) store coverage is product (brand) and not segment or company specific.

4 Estimating Market Power

There is a long history of mapping market share structure into market power.[16] In the case of a Cournot oligopoly homogeneous good industry one can show with N firms that the average price-cost margin in the industry is written as,

$$\sum_j s_j \left(\frac{p - c_j}{p} \right) = \frac{\sum_j s_j^2}{\eta} = \frac{HHI}{\eta} \tag{1}$$

where s_j is the firm j market share, η denotes the industry demand elasticity, p is the industry price and c_j is the marginal cost firm j faces. Market power in an industry with homogenous goods is directly and positively linearly related to the HHI. While the HHI may be a good rule of thumb to use in deciding whether or not to investigate mergers in homogenous industries, once one introduces differentiated goods, mapping HHI to market power becomes more problematic.

In differentiated products industries, market share is no longer a good approximation of the ability to mark-up price over cost. The market is now made up of a number of products that are differentiated, either by location or some product attributes. Some products are more similar than others in terms of these attributes. The competitive constraint on a firm's pricing is now determined by the degree of substitutability between the various goods in the market. Things become even more complex in the case that firms produce multiple products in the market. Firms may specialize in producing goods with very similar attributes, or have a portfolio of goods with very different attributes, and may or may not locate alongside other multi-product firms producing similar or different goods. The HHI for the market tells us little about the underlying structure of such markets or the market power of firms. Firms with small market share may well be able to extract high price-cost mark-ups by being specialized in their product characteristics and location. The question now arises as to how we may map this complexity of multi-product firms operating over product characteristics and locations into market power?

In order to evaluate market power where products are differentiated, it is necessary to estimate the degree of substitutability between the various goods in the market. However, estimating demand for differentiated products has a dimensionality problem. A linear demand system for J brands has J^2 price parameters to estimate. One must therefore place some structure on the estimation. A number of alternative demand specifications have been developed to deal with this dimensionality problem by reducing the dimensionality space into a product space. We focus our attention on discrete choice models used in estimating demand for differentiated products.[17] The next section outlines how we estimate demand primitives for differentiated products. In addition, given demand primitives we see how to back-out price cost margins that are consistent with a structural model of multi-product companies pricing in a Nash equilibrium.

4.1 Structural models

The discrete choice literature has gained a level of reliability that represents the best option to estimate reliable primitives of demand in a differentiated products industry. Logit, Nested Logit and Random Coefficient models are at the centre of this literature. In our paper we drop the Logit model due to issues surrounding *Independence of Irrelevant Alternatives*. We embed both the Nested Logit and Random Coefficient models into a general indirect utility.[18]

This section outlines the Nested Logit model in Mariuzzo, Walsh and Whelan (2003). In addition, we outline details of our Random Coefficient model, which extends BLP and Nevo (2001), in Mariuzzo, Walsh and Whelan (2005). An important feature that characterizes both our models is that, unlike previous papers using market level data, we control for the effect of the traditional form of product differentiation coming from product locations across stores of the market. In particular, Mariuzzo, Walsh and Whelan (2005) show how to construct a distribution of consumers closeness to each product from information on product effective coverage of stores.

We write the random utility of consumer i for brand j as the sum of a mean utility (δ_j), an individual deviation from that mean (μ_{ij}) and an error component (ε_{ij}) which is assumed to be an identical and independently distributed extreme value function. The time subscript t is omitted purely to avoid cumbersome notation but is present in our estimates. The utility can therefore be written as,

$$
\begin{aligned}
u_{ij} &= \delta_j + \mu_{ij} + (1-\rho)\,\varepsilon_{ij} \\
\delta_j &= \mathbf{x}_j'^1\boldsymbol{\beta} - \left[\alpha_1 * ln(D_j) + \alpha_0\right] p_j + \beta_{K+1} ln(D_j) + \xi_j \\
\mu_{ij} &= \zeta_{ig} + \boldsymbol{\nu}_i'^A\mathbf{X}_j^2\boldsymbol{\sigma}_A + \boldsymbol{\nu}_{ij}'^C\mathbf{X}_j^2\boldsymbol{\sigma}_C + \boldsymbol{\nu}_i'^N\mathbf{X}_j^2\boldsymbol{\sigma}_N \qquad (2)
\end{aligned}
$$

where p_j is price of product j and $\mathbf{x}_j^1$ is a column vector of K observed product characteristics (including the constant) that enter linearly in our estimates, whereas $\mathbf{X}^2$ is a matrix in which the diagonal includes a subset of the previous characteristics that enter nonlinearly in a second stage of the estimation procedure (in our model this is a diagonal matrix having along the diagonal the constant and prices). Some of the product characteristics (ξ_j) are unobserved to us but are observed by our consumers in their choices.

For the more general Random Coefficient model, let $\alpha_1 = \beta_{K+1} = \rho = \zeta_{ig} = 0$. This ensures that an individual deviation from mean utility (μ_{ij}) is driven by distributions in consumer demographics or Random Coefficients on the constant and prices. Subscripts (and superscripts) A, C, N stand for, *Age*, *Closeness to Stores*, and a *(Log) Normal distribution,* respectively, which individualize our (ns) simulated (observed and unobserved) consumers characteristics. Consumer taste for location (the probability that the product will be in the nearest store) is captured in our utility function at an individual level, by the closeness variable ν_{ij}^C (which is consumer i and brand j specific). The idea is that distance has a direct effect on utility by way of an interaction with the constant, but also enters as an interaction with prices. The reason for this interaction is that one should expect price sensitivity to increase with store coverage. Our simulations are drawn from different distributions assumed to be independent and characterized by different variability. The *Age* distribution only varies over time and is the same for all variables entering $\mathbf{X}_j^2$ ($\boldsymbol{\nu}_i^A = \left[\nu_i^A, \nu_i^A\right]'$); the *Normal* distribution varies itself only over time but its distributions are different for each component of $\mathbf{X}_j^2$ ($\boldsymbol{\nu}_i^N = \left[\nu_i^N, \nu_i^{LN}\right]'$) where the normal distribution is linked to the constant and the lognormal distribution is associated to the price variable; the *Closeness to Stores* distribution varies both over time and over brands but is the same for each component (Constant and Price) of $\mathbf{X}_j^2$ ($\boldsymbol{\nu}_{ij}^C = \left[\nu_{ij}^C, \nu_{ij}^C\right]'$).[19]

The augmented Nested Logit model is obtained by setting $\boldsymbol{\sigma}_A = \boldsymbol{\sigma}_C = \boldsymbol{\sigma}_N =$

$\mathbf{0}$, and allowing $\alpha_1, \beta_{K+1}, \rho, \zeta_{ig}$ to be non-zero. This will still incorporate product specific locations into our model as part of the mean utility. This latter effect is the result of an average over individuals $D_j = \frac{100}{N}\sum_{i=1}^{N} d_{ij}$, where d_{ij} is a dummy equal one when brand j is available in individual i's nearest shop. We allow D_j to have a direct effect on mean utility and an indirect effect through an interaction with prices. For consumers, ζ_{ig} is utility common to all brands within a group g and has a distribution function that depends on ρ, with $0 \leq \rho < 1$. As the parameter ρ approaches one, the within group correlation of utility levels across products goes to one (products within groups are perfect substitutes). As ρ tends to zero, so too does the within group correlation.[20] Finally, since we are dealing with discrete choice models, we need to define an utility for the outside good,

$$u_{i0} = \underbrace{\xi_0}_{\delta_0} + \underbrace{\sigma_0 \nu_{i0}}_{\mu_{io}} + \epsilon_{i0} \tag{3}$$

and following the literature, we normalize $\xi_0 = \sigma_0 = 0$. The demand parameters to be estimated are $\{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}, \rho\}$. Given the above utility function, one can derive a demand function. The procedure requires integrating the utility over the error structure and normalizing it over the outside option. This leads to a probability (ϕ_{ij}) that individual i buys brand j over the J available brands and averaging over ns simulated individuals (and knowing the number of individuals in the economy),

$$\begin{aligned} s_j(\cdot) &= \left(\frac{1}{ns} \sum_{i=1}^{ns} \underbrace{\left(\frac{e^{\delta_j(\cdot)+\mu_{ij}(\cdot)}}{1+\sum_{j=1}^{J} e^{\delta_j(\cdot)+\mu_{ij}(\cdot)}} \right)}_{\phi_{ij}} \right), \text{ for } j \in J \\ q_j(\cdot) &= N s_j(\cdot). \end{aligned} \tag{4}$$

The demand derived in (4) represents a general structure. If one wants to recover the demand for the Nested Logit model or from the Random Coefficient model, the following simplifications are to be added:

- Impose $\boldsymbol{\sigma}_A = \boldsymbol{\sigma}_C = \boldsymbol{\sigma}_N = \mathbf{0}$ in (2), then the Nested Logit Model has the closed form solution (see Berry (1994)),

$$ln(s_j) - ln(s_0) = \mathbf{x}_j' \boldsymbol{\beta} - \alpha_0 p_j - \alpha_1 \left[p_j * ln(D_j)\right] + \beta_{K+1} ln(D_j) + \rho \ln(s_{jg}) + \xi_j \quad (5)$$

where s_j, s_0, s_{jg} are the market shares of brand j, the market share of the outside good 0 and the market share of brand j in segment g, respectively.

- Impose $\alpha_1 = \beta_{K+1} = \rho = \zeta_{ig} = 0$, then the more general Random Coefficient model has a structure similar to (4). 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. This generalization of the model comes however at the price of increasing the computational complexity requiring non linear estimators and numerical solutions based on contraction mapping and simulations together with a nonlinear two-step GMM estimator. The first stage of the econometric procedure simultaneously estimates the demand and cost function parameters (see description of cost at the end of this section)

$$\begin{aligned} ln(s_j) - ln(s_0) &= \mathbf{x}_j' \boldsymbol{\beta} - \alpha_0 p_j + \xi_j \\ \ln(c_j) &= \mathbf{w}_j' \boldsymbol{\gamma} + \omega_j \end{aligned} \quad (6)$$

  Given some starting value of the non linear parameters, α_0 and those associated with deviations from the mean $(\boldsymbol{\sigma}_A, \boldsymbol{\sigma}_C, \boldsymbol{\sigma}_N,)$; the estimation of the $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ parameters allows us to back out the demand unobservable (using simulations and contraction mapping techniques) and, via a structural model of equilibrium, the cost function unobservable, where $\mathbf{w}$ are the observed cost characteristics, by product, $(\widehat{\xi}_j, \widehat{\omega}_j)$. Imposing an assumption of conditional independence $E(\xi_j|z) = E(\omega_j|z) = 0$ (where z are our instruments), one applies a second step procedure that searches for the non linear parameters that minimize the distance of ξ_j and ω_j from zero.

The main reason for estimating reliable demand parameters is to compute own and cross-price elasticities which reveal the underlying substitution effects.

The general formula for own and cross-price elasticities is,

$$\begin{aligned}
\frac{\partial s_j\left(\cdot\right)}{\partial p_j}\frac{p_j}{s_j} &\equiv \varepsilon_{jj} = \left(\frac{1}{ns}\sum_{i=1}^{ns}\phi_{ij}\left(1-\phi_{ij}\right)\frac{\partial u_{ij}}{\partial p_j}\right)\frac{p_j}{s_j} \\
\frac{\partial s_j\left(\cdot\right)}{\partial p_b}\frac{p_b}{s_j} &\equiv \varepsilon_{jb} = -\left(\frac{1}{ns}\sum_{i=1}^{ns}\phi_{ij}\phi_{ib}\frac{\partial u_{ib}}{\partial p_b}\right)\frac{p_b}{s_j} \qquad (7)
\end{aligned}$$

which in the case of the Nested Logit can be simplified to the closed form,

$$\begin{aligned}
\varepsilon_{jk} &= \left[\alpha_0+\alpha_1\ln(D_j)\right]\left[s_k+\frac{\rho}{1-\rho}s_{jg}\right]p_k \quad if\ k\neq j \text{ and } j,k\in g \\
\varepsilon_{jk} &= \left[\alpha_0+\alpha_1\ln(D_k)\right]p_k s_k \quad if\ k\neq j \text{ and } k\notin g \\
\varepsilon_{jj} &= \left[\alpha_0+\alpha_1\ln(D_j)\right]\left[s_j-\frac{1}{1-\rho}+\frac{\rho}{1-\rho}s_{jg}\right]p_j \text{ if } k=j \qquad (8)
\end{aligned}$$

It is important to note that the elasticities here refer to the percentage change in market share in response to a one per cent change in price. We estimate the demand side primitives and, via an equilibrium pricing system of equations, to be defined, we can back out the price cost mark-up (Lerner Index) for each brand. Firms maximize the sum of profits accruing from firm brands. In brand price setting, p_j, a firm takes the price of all other firms' brands as given. The firm f internalizes the cross-price effect on market share of the brands it owns (J_f) in the price setting of an individual brand,

$$\prod\nolimits_f = \sum_{j\in J_f}\left(p_j q_j\left(\cdot\right)-c_j q_j\left(\cdot\right)\right) \qquad (9)$$

the maximization of which leads to the first order conditions from which we get our price equilibria,

$$\mathbf{p}=\mathbf{c}+\underbrace{\Delta^{-1}\mathbf{s}}_{markup} \qquad (10)$$

where Δ is defined as,

$$\Delta_{jb}=\begin{cases}\frac{-\partial s_b(\cdot)}{\partial p_j}, & \text{if brands } b,j \text{ are produced by the same firm} \\ 0, & \text{otherwise.}\end{cases} \qquad (11)$$

Two alternative approaches are available to back out the markup. A first approach is a simplified version where the mark-up is backed out directly from the demand side via the augmented Lerner index (Mariuzzo, Walsh and Whelan (2003)). An alternative (more complex) approach requires a simultaneous estimation of demand and marginal cost (see Mariuzzo, Walsh and Whelan (2005)). A simultaneous estimation of demand and cost not only increases efficiency in the estimates, but also gives us good instruments to better identify the (price and interactions) parameters.[21]

5 Comparing Results of Nested Logit and BLP Models

We estimate the Nested Logit demand system in equation (5). Estimates are 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 results are presented in Table 3. In column I we present a Nested Logit model using no data on product locations across stores in the regression or in the instrument set. In column II we estimate the full model in equation (5). In both specifications, the Chi-squared test rejects the null that the moments (instruments) are invalid. We estimate $\alpha_j = (-2.9 - .63 * \ln(D_j))$. This implies from equation (8) that corresponding Nested Logit own-price and cross-price elasticities will be augmented by product specific share of consumers that can find the product in their nearest store[22]. In addition, we estimate $\rho = 0.65$, 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. These estimates provide a matrix of Nested Logit own-price and cross-price elasticities, of which there are J^2 in each bi-monthly period.

The results of the BLP procedure, 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. With reference to utility, we estimate the mean effect of our product characteristics, the coefficient on price, the parameters that define individual variability in taste for a benchmark quality and price, and the interaction terms. Our specification of the utility and cost function, choices of demand and supply side instruments and our structural model of equilibrium predict 80 per cent of the variation in the actual market share of each product in each time period. 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 efficient estimates of our coefficients on price and consumer taste distributions interactions with price. These determine our estimates of the own and cross-price elasticities set out in equation (7). The coefficient on price and the interaction of price with our consumer taste distributions that reflect consumer taste for closeness are highly significant. The market level consumer taste distributions interactions 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 that carry the product reflects closeness to consumers. We see clearly a trade off between covering the market and the nature of price competition that a brand faces, a typical trade-off in the theoretical literature on product differentiation. Less coverage is not a good attribute in terms of market share but can potentially lead to higher price cost markups by making own- and cross- price elasticities less responsive to the prices of other brands. Even though the market level interactions do not come in, we see that our product level consumer taste distribution for geography induces rich demand primitives.

In Table 5 we compare the demand primitives that result from the Nested Logit demand system and the BLP demand model, estimated jointly with supply. We average over the brands within each of our flavor, packaging and diet segments. This in turn is averaged over our 28 bi-monthly periods. The elasticity of market share with respect to the own-price elasticities are similar in trends for both models, though the BLP estimates tend to be more elastic. In addition, both models estimate that the own price elasticity is more elastic for Cans relative to other packaging types, while 2-litre packaging is the most inelastic. We also report the sum of the cross-price elasticities for each brand, averaged by segment. The BLP model clearly estimates these to be larger.

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 conditions in equation (10), one can get estimates of a Lerner Index per brand/product j. Aggregating these estimates over different sets of brands gives an indicator of firm or segment market power. In Table 6 we compare estimates of bi-monthly mark-ups and profits, averaged over the period, by segment. The key characteristic is packaging type. Packaging with 1.5 and 2-Litre bottles earn greater markups than (cans and Standard bottles). Diet drinks seem to also get a premium and the mark-ups are very similar when one compares both frameworks.

In Table 7 we compare estimates of bi-monthly mark-ups and profits, averaged over the period, by company. We document the price cost mark-ups and market shares by company for the retail carbonated soft drinks market using estimates of demand primitives from our Nested Logit and BLP frameworks. Clearly a monotonic relationship between market power and market share does not exist in this industry. Companies with a smaller share of the carbonated soft drinks market extract rents, within the product segments and stores of the market they operate in, comparable to that of multinationals who 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.

5.1 Implications for EU Merger Control

In Table 7 we document the HHI measures of concentration in terms of market shares and in terms of profit shares for each company. This is done for both the Nested Logit and BLP model. We take a hypothetical merger in our data, companies ranked 4 and 5, to illustrate that merger screening based on dominance of market shares may fail to identify, in terms of market power, a damaging merger. In addition, we take a hypothetical merger in our data, companies ranked 1 and 7, to illustrate that merger screening based on a dominance test may select a merger for investigation that has insignificant market power implications.

Using the rules outlined in Table 1 we observe that both models suggest that the proposed merger between the companies ranked 4 and 5 should be investigated on the basis of the HHI on profit shares. This is not the case if one only used information on market share. Companies small in output can have significant market power by been specialized into geographic and/or product segments. In addition, using the thresholds, a proposed merger between the companies ranked 1 and 7 should not be investigated on the basis of the HHI on profit shares. This would not be the case using the market share of companies output.

Our policy recommendation is to use a structural model to estimate company mark-ups (aggregated over products) in differentiated goods industries. Mergers should be assessed on the basis of market power, and not market share, considerations as part of selection or screening of notified mergers. Merger screening may fail to identify damaging mergers using the market share of companies output without any market power considerations. In most industries we see waves of mergers among small companies that go unchecked, which may have significant market power considerations. In addition, merger screening using the market share of companies may select mergers for investigation that have little market power implications. In the EU and US we see very few of the selected mergers actually blocked. This must be a sign that selection based on output shares is an imperfect indicator of competitive concerns.

6 Conclusions and Recommendations

Recent EU Merger Control Regulation No 139/2004 moves the EU criteria closer to the US practice, where mergers are prohibited if they would result in a *"substantial lessening of competition"*. While this move away from a dominance test may be apparent during the investigation of mergers, we highlight the fact that an analysis of market concentration is still at the centre of the preliminary selection stage of all notified mergers in the EU and US. This paper illustrates that the HHI measures of output concentration is not a good indicator of market power in differentiated product industries. The complex operation of multi-product firms over different product and geographic segments in these industries means that there is no theoretical foundation for the mapping of market concentration into market power. This clearly has implications for the use of the HHI and changes in HHI based on market shares as a screening device for proposed mergers. We undertake a proposed merger between two firms that has little impact on the overall HHI measure of output concentration for an industry, and thus would not be likely to undergo an investigation by Anti-trust authorities using the current thresholds. Yet, we show a big increase in market power as the companies, small in output, are specialized into geographic and/or product segments. In the event that a merger results from the aggregation over companies with high mark-ups, irrespective of their overall share in the market, our profit share indicator of market power using the HHI is clearly desirable in the screening stage of mergers in differentiated products industries. In addition, we demonstrate the other scenario where a merger without market power concerns is selected for investigation by Anti-trust authorities using the current thresholds. Given the low selection rate, it seems very costly to select mergers that will clearly not be blocked during investigation.

This paper compares a simple and a more advanced structural approach in the estimation of market power. Our simple model is straightforward to implement, not requiring cumbersome estimation procedures or a heavy data burden.[23] More importantly the results are similar to that estimated in the BLP model. Using estimates of market power to construct HHI in profit shares allows more accurate and informed decisions in the screening stage as to which mergers should undergo investigation. This will ensure a simple screening technique that can identify a threat to competition among notified mergers.

Notes

[1]The European Commission has exclusive jurisdiction for mergers between firms with a combined worldwide turnover of at least 5 billion euros and a turnover within the European Economic Area of more than 250 million euros for each of them. Not meeting these turnover thresholds, or other criteria, may result in a merger to be assessed in an individual EU country.

[2]The HHI is the sum of the squares of firm percentage output market share, which gives proportionately greater weight to larger players in the market. It ranges from close to zero (in an atomistic market) to 10000 (in the case of monopoly). The post-merger HHI assumes the market share of the merging parties is the sum of market share of the two undertakings. This does not allow for strategic responses to the merger in terms of price or quantity changes or industry dynamics in terms of entry or exit. The change in the HHI just reflects summing the market shares of the merging firms.

[3]The HHI would now be the sum of the squares of the firm's profit shares, ranging from close to zero (no rents in the market) to 10000 (monopolistic rents). The post-merger HHI assumes the profit share of the merging parties is the sum of the two undertakings. This does not allow for economies of scale or any other strategic reason for the merger. Hence, the change in the HHI just reflects summing the coming together two companies ex-ante profit shares.

[4]In the US 17,404 transactions were notified between 1998 and 2002, and only 2% where selected for enforcement actions.

[5]This replaces Article 2 of regulation No 4064/1989, the *"dominance"* test which indicated that any merger that *"creates or strengthens a dominant position as a result of which effective competition would be significantly impeded"* is to be blocked.

[6]By *"increased market power"* is meant *"the ability of one or more firms to profitably increase prices, reduce output, choice or quality of goods and services, diminish innovation, or otherwise influence parameters of competition"* (EU merger guidelines 2004/C 31/03 , No 8).

[7]This may arise for example when merging firms have large market share; merging firms are close competitors; customers have limited means of switching suppliers (see EU merger guidelines No 26 - 38).

[8]The EU merger guidelines outline three necessary conditions for sustainable coordination (i) ability to monitor coordinating firms and whether they are keeping an agreement (ii) credible punishment deterrent mechanism if a deviation is detected (iii) reactions of outsiders (current / future competitors) can not jeopardise expected gains from coordination.

[9]As with the US horizontal merger guidelines, the EU merger guidelines acknowledge the importance of considering the relevant market for analysis. For definition of relevant market for purpose of community competition law, see OJ C 372, 9.12.1997, p3, paragraphs 54-55. Once the relevant geographic

and product market have been defined, a preliminary screening of all notified mergers takes place.

[10]Normally current market shares are used in the analysis. However, these may be adjusted to reflect reasonable certain future changes e.g. in light of entry, exit or expansion. [See e.g. Case COMP/M.1806 - Astra Zeneca /Novartis points 150 and 415].

[11]Case T-221/95, Endemol v Commission, (1999) ECR II-1299, paragraph 134 and Case T-102/96, Gencor v Commission (1999) ECR II-753, paragraph 205. It is a distinct question whether a dominant position is created or strengthened as a result of the merger.

[12]Thus, Commission has found cases where mergers resulting in firms holding market shares between 40% and 50% [COMP/M.2337 - Nestle/Ralston Purina, points 48-50] and even <40% [Commission decision 1999/674/EC in CaseIV/M.1221 - Rewe/Meinl, OJ L 274, 23.10.1999, p1, points 98-114; Case COMP/M.2337 - Nestle/Ralston Purina, points 44-47] to lead to the creation or strengthening of a dominant position.

[13]This was done for (i) all cases where Commission established dominance (ii) all cases where Commission accepted remedies in Phase I on the basis of serious doubts (note that '*serious doubts*' is the substantive standard for opening a phase II investigation) (iii) all Phase I clearance cases in 2002. In total, the analysis was based on data from 1231 markets from 207 cases [377 markets from 60 '*dominance*' cases; 273 remedies markets and 356 clearance markets].

[14]The most common examples of *"special circumstances"* were cases where one of the merging parties was a recent entrant, or where a large firm acquired a relatively small firm.

[15]Since the post-merger HHI and change in HHI are most significant in evaluating mergers with straightforward horizontal effects, the table omits those mergers challenged on basis of other competitive theories e.g. those based on vertical control, monopsony power, elimination of potential competition, or where competitive concerns stemmed from influence through partial ownership and aspects of corporate governance.

[16]This idea is evident with the structure-conduct-performance paradigm of Bain in the 1950s, positing a one-way mapping from structure (concentration of market share) to conduct (treated as a black box) to performance (average price-cost mark-up across companies in an industry).

[17]As an alternative one could use representative consumer choice. These models include the Distance Metric model (Pinkse, Slade and Brett, 2002; Pinkse and Slade 2002), or the Multi-Stage Budgeting model (Hausman, Leonard and Zona, 1994).

[18]Anderson and de Palma (1992) is a good textbook for a detailed analysis on these models.

[19]Unfortunately, as noticed by Berry Levinsohn and Pakes (2004) and Petrin

(2002), a reliance on the market-level distributions of consumer characteristics do not give us the degrees of freedom associated with micro-level data on individual choices. Moreover, 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. In our example we improve our estimates of demand primitives by randomizing over data on store coverage to create a distribution of consumer disutility reflecting distance to each brand (product). We have a distribution of consumer preferences that reflects the likely convenience of the location of retail stores that carry the product in question. The interaction of this product (j) specific distribution with prices can be estimated with far greater degrees of freedom when compared to interactions using market level distributions of consumer characteristics. This will result in a very rich set of demand primitives.

[20]When $\rho = 0$ this reduces to the ordinary logit model, where substitution possibilities are completely symmetric, for example as when all products belong to the same group.

[21]Nevo (2000) practitioners guide is a good reference to understand the estimation procedure. We extend his Matlab program to undertake a BLP estimation on our specific functional forms.

[22]These estimates are slightly different compared to Mariuzzo, Walsh and Whelan (2003) as we use packaging X month dummies instead of packaging X season dummies. In addition we use a different set of instruments. This makes our Nested Logit model including the interaction term for distance to a product comparable to the Demand model of BLP.

[23]For the use of the structural models using a model of supply and demand (Nested Logit) in the investigation stage of a merger, see Ivaldi and Verboven (2002) on the Volvo/Scania case.

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Table 1: EC and US Screening Thresholds

	HHI	*Δ HHI*
EC Screening Thresholds		
Competitive Concern	1000 - 2000	> 250
Competitive Concern	> 2000	> 150
US Screening Thresholds		
Competitive Concern	1000 - 1800	> 100
Competitive Concern	> 1800	>50
No Competitive Concerns for HHI < 1000 for any Δ HHI		

Table 2: US Data for Fiscal Years 1999—2003 on Individual Relevant Markets in Cases in which the Agencies Challenged Mergers

Ex-Ante Merger HHI	Change in the HHI								
	0-99	100-199	200-299	300-499	500-799	800 - 1,199	1,200 - 2,499	2,500+	Total
0-1,799	0	17	18	19	3	0	0	0	57
1,799-1,999	0	7	5	14	14	0	0	0	40
2,000-2,399	1	1	7	32	35	2	0	0	78
2,400-2,999	1	5	6	18	132	34	1	0	197
3,000-3,999	0	3	4	16	37	63	53	0	176
4,000-4,999	0	1	3	16	34	30	79	0	163
5,000-6,999	0	2	4	16	9	14	173	52	270
7,000+	0	0	0	2	3	10	44	223	282
Total Cases	2	36	47	133	267	153	350	275	1263

Table 3: Estimation of Demand: Nested Logit Model of Demand.

Dependent Variable: $\ln(S_j) - \ln(S_0)$	Regression I		Regression II	
	Coefficient	(t-stat)	Coefficient	(t-stat)
Constant	-0.8	(1.0)	-3.7	(10.1)*
Default Cola				
Orange	1.1	(12.5)*	0.59	(9.6)*
Lemonade	0.14	(1.6)	-0.01	(0.2)
Mixed Fruit	0.45	(5.3)*	0.04	(0.6)
Default Cans				
Standard	2.7	(7.9)*	1.2	(6.7)*
1.5 Litre	3.4	(9.7)*	1.7	(8.9)*
2 Litre	-0.3	(1.1)	-0.11	(0.7)
Multi-Pack Cans	0.2	(0.5)	0.8	(3.8)*
Default Diet				
Regular	2.2	(3.5)*	1.6	(4.2)*
$+\beta_{k+1} \ln(D_{jt})$			1.2	(9.6)*
$\rho \ \ln(s_{gjt})$ [a]	0.91	(13.1)*	0.65	(9.6)*
$-\alpha_1 \ln(D_{jt})\, p_{jt}$ [a]			0.63	(7.5)*
$-\alpha\, p_{jt}$ [a]	5.9	(9.1)*	2.9	(7.4)*
Company Dummies	Yes		Yes	
Packaging × *Month* Dummies	Yes		Yes	
R^2	0.61		0.81	
Numbers of Observations	4,645		4,645	
Over-identification IV Test	$\chi^2(5) = 0.99$		$\chi^2(5) = 0.99$	

[a] Instruments for Regression I include all the regressors, with the exception of p_{jt} and $\ln(s_{gjt})_t$. Inventories$_{jt}$; Hausman-Taylor instrumental variables (brands of the same firm in other segments) with respect to p_{jt}, and Inventories$_{jt}$; and BLP instruments (brands of the other firms in the same segment) with respect to mean and standard deviation of Inventories$_j$

Instruments for Regression II include all the regressors, with the exception of p_{jt} , $\ln(s_{gjt})$ and $\ln(D_{jt})p_{jt}$. Inventories$_{jt}$; Hausman-Taylor instrumental variables (brands of the same firm in other segments) with respect to p_{jt}, $\ln(D_{jt})$, and Inventories$_{jt}$; and BLP instruments (brands of the other firms in the same segment) with respect to mean and standard deviation of $\ln(D_{jt})$ and Inventories$_j$. *Significantly different from zero at the five percent level in a two-tailed test.

Table 4: Estimation of Demand and MC Equation: BLP Specification

		Demand	Cost
	Variables	**Coefficient (t-stat)**	**Coefficient (t-stat)**
Means			
	Constant	-6.2 (6.1)*	0.13 (.70)
	Inventories		-.20 (2.7)*
	Store Coverage		.11 (2.8)*
	Price	-7.3 (6.8)*	
Default Cola	**Orange**	1.3 (15.6)*	.02 (.40)
	Lemonade	.69 (6.4)*	.16 (2.7)*
	Mixed Fruit	1.7 (6.5)*	-.22 (2.9)*
Default Cans	**Standard**	4.5 (3.6)*	.33 (3.2)*
	1.5 Litre	4.8 (3.5)*	.39 (5.1)*
	2 Litre	.78 (3.4)*	-1.1 (4.3)*
	Multi-Pack Cans	-3.4 (12.2)*	-1.2 (6.2)*
Default Diet	**Regular**	.71 (11.8)*	.08 (1.3)
Distribution Interactions			
Parametric	**Constant**	3.4 (3.4)*	
	Price	-0.7 (.61)	
Age	**Constant**	-11.6 (2.8)*	
	Price	-2.1 (0.3)	
"Closeness to Stores"	**Constant**	29.1 (18.6)*	
	Price	-11.2 (7.8)*	
R^2		***.82***	
GMM Objective		.0073	
# Negative Predicted Mark-Ups			0
# of Simulations		100	

Demand and Cost Side include Firm and Packaging X Month Dummies. Observations 4,645. Instruments for Demand: Flavour, 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; and BLP instruments (brands of the other firms in the same segment) with respect the Mean and Standard Deviation of store coverage and inventories. Instruments for Supply: Same as demand expect the Hausman-Taylor instrumental variables.

Table 5*: Segment (Weighted Averages over Brands) 1992-1997*

*Nested Logit Demand Model

** BLP Demand and Supply Model

Segment	Own Price Elasticity *	Sum of Cross Price Elasticity*	Own Price Elasticity **	Sum of Cross Price Elasticity**
Cola Cans	-13.408	2.9194	-13.296	6.63
Cola Standard	-11.384	2.4329	-8.3307	3.5272
Cola 1.5 Litre	-5.8557	1.3155	-6.3414	5.6982
Cola 2 Litre	-4.1667	0.82662	-5.4398	7.1344
Cola Cans Multipacks	-7.9963	1.7595	-9.8501	6.8057
Orange Cans	-11.621	2.5775	-13.45	6.9458
Orange Standard	-11.315	2.4595	-14.791	7.2123
Orange 1.5 Litre	-5.8679	1.2974	-8.2648	7.9649
Orange 2 Litre	-4.4812	0.93835	-6.0833	7.4632
Orange Cans Multipacks	-8.8926	2.0043	-12.798	8.3505
Lemonade Cans	-8.9282	2.0273	-7.2687	4.5024
Lemonade Standard	-11.926	2.6369	-15.899	8.1024
Lemonade 1.5 Litre	-5.6547	1.2635	-5.7796	5.7165
Lemonade 2 Litre	-3.9762	0.81921	-5.2258	7.1708
Lemonade Cans Multipacks	-8.1858	1.8823	-6.8013	4.7672
Mixed Fruit Cans	-12.276	2.7094	-16.43	8.2662
Mixed Fruit Standard	-14.400	2.9623	-12.723	6.2424
Mixed Fruit 1.5 Litre	-6.3776	1.4034	-8.2566	6.6438
Mixed Fruit 2 Litre	-4.0611	0.73015	-5.4653	6.9214
Mixed Fruit Cans Multipacks	-5.3052	1.2756	-9.4387	6.0243
Diet Segments				
Cola Cans	-11.817	2.6649	-11.757	6.4163
Cola Standard	-12.303	2.8268	-15.268	8.3488
Cola 1.5 Litre	-5.7972	1.3042	-5.023	3.5868
Cola 2 Litre	-4.2643	0.93494	-6.3843	7.6129
Cola Cans Multipacks	-8.7069	1.9573	-12.888	8.173
Orange Cans	-10.997	2.6402	-14.889	8.5435
Orange Standard	-9.9561	2.3916	-14.792	8.0678
Orange 1.5 Litre	-5.4339	1.3054	-8.4619	8.2154
Orange 2 Litre	-4.6477	1.0488	-6.9119	7.4193
Lemonade Cans	-13.181	3.0485	-9.5058	4.6999
Lemonade Standard	-12.029	2.883	-15.778	8.3728
Lemonade 1.5 Litre	-6.9400	1.6513	-8.5238	8.0661
Lemonade 2 Litre	-4.7671	1.0658	-3.9351	4.2408
Lemonade Cans Multipacks	-7.5778	1.8211	-11.733	7.9479
Mixed Fruit Cans	-9.0504	2.0883	-14.292	8.1215
Mixed Fruit Standard	-9.2219	2.1273	-14.234	8.4596
Mixed Fruit 1.5 Litre	-4.8644	1.4551	-6.8668	7.4791
Mixed Fruit 2 Litre	-4.1952	1.0073	-11.757	6.4163

Table 6*:* Segment (Weighted Averages over Brands) 1992-1997
*Nested Logit Demand Model
** BLP Demand and Supply Model

Segment	Segment Share of Output	Price per Litre	Estimated Mark-Up*	Estimated Bi-Monthly Profit in £IR(000)*	Estimated Mark-Up**	Estimated Bi-Monthly Profit in £IR(000)**
Cola Cans	4.22	1.43	0.05	99.82	0.09	185.31
Cola Standard	3.78	1.26	0.08	123.69	0.10	167.56
Cola 1.5 Litre	2.53	0.75	0.13	86.14	0.16	103.19
Cola 2 Litre	11.1	0.50	0.22	411.28	0.22	435.13
Cola Cans Multipacks	1.92	0.96	0.16	103.56	0.14	83.62
Orange Cans	1.85	1.38	0.08	67.66	0.08	67.11
Orange Standard	2.10	1.27	0.08	78.13	0.08	72.22
Orange 1.5 Litre	2.22	0.68	0.17	86.64	0.13	69.35
Orange 2 Litre	8.51	0.46	0.25	327.23	0.20	270.2
Orange Cans Multipacks	0.49	0.97	0.14	23.85	0.11	19.12
Lemonade Cans	1.41	1.41	0.06	36.41	0.09	61.4
Lemonade Standard	1.38	1.16	0.13	65.57	0.09	52.43
Lemonade 1.5 Litre	3.75	0.71	0.14	126.49	0.17	151.19
Lemonade 2 Litre	11.8	0.47	0.29	503.17	0.23	429.55
Lemonade Cans Multipacks	0.36	0.97	0.13	16.43	0.13	15.36
Mixed Fruit Cans	2.13	1.39	0.07	72.67	0.07	71.1
Mixed Fruit Standard	6.29	1.37	0.08	198.65	0.07	208.64
Mixed Fruit 1.5 Litre	1.80	0.74	0.18	73.51	0.12	56.62
Mixed Fruit 2 Litre	18.8	0.41	0.0	786.74	0.22	565.8
Mixed Fruit Cans Multipacks	0.02	0.83	0.17	1.06	0.28	1.05
Diet Segments						
Cola Cans	1.11	1.39	0.09	48.14	0.09	47.23
Cola Standard	0.93	1.30	0.08	34.05	0.11	43.84
Cola 1.5 Litre	0.83	0.75	0.15	31.93	0.16	35.33
Cola 2 Litre	2.85	0.55	0.28	149.57	0.22	118.13
Cola Cans Multipacks	0.63	0.6	0.17	37.21	0.14	27.56
Orange Cans	0.23	1.27	0.10	10.91	0.07	7.64
Orange Standard	0.05	1.19	0.12	2.08	0.26	1.68
Orange 1.5 Litre	0.21	0.71	0.18	9.71	0.13	6.56
Orange 2 Litre	0.72	0.56	0.22	31.74	0.18	23.89
Lemonade Cans	0.53	1.44	0.07	18.10	0.08	22.5
Lemonade Standard	0.21	1.29	0.10	9.07	0.10	9.91
Lemonade 1.5 Litre	1.62	0.73	0.14	58.18	0.18	66
Lemonade 2 Litre	3.40	0.59	0.20	139.92	0.22	141.25
Lemonade Cans Multipacks	0.21	0.96	0.14	9.60	0.13	8.71
Mixed Fruit Cans	0.04	1.27	0.10	1.73	0.09	1.59
Mixed Fruit Standard	0.04	1.17	0.11	1.86	0.08	1.31
Mixed Fruit 1.5 Litre	0.01	0.83	0.17	0.09	0.54	0.22
Mixed Fruit 2 Litre	0.11	0.55	0.24	5.20	0.22	4.78

Table 7: Company Mark-ups, Output and Profit shares, in the last period.
*Nested Logit Demand Model
** BLP Demand and Supply Model

Companies	Brands	Output Share	Mark-Up (NL*)	Profit Share (NL*)	Mark-Up (BLP**)	Profit Share (BLP**)
Rank 1	51	0.4792	0.15	0.3693	0.14	0.4600
Rank 2	36	0.2337	0.22	0.2655	0 .13	0.2000
Rank 3	20	0.0928	0.28	0.1326	0.18	0.1100
Rank 4	4	0.0589	0.30	0.0911	0.25	0.1500
Rank 5	3	0.0553	0.32	0.0907	0.29	0.0500
Rank 6	7	0.0343	0.16	0.0285	0.10	0.0100
Rank 7	3	0.0229	0.05	0.0054	0.05	0.0100
Rank 8	5	0.0196	0.14	0.0144	0.10	0.0010
Rank 9	6	0.0028	0.15	0.0022	0.13	0.0002
Rank 10	1	0.0001	0.10	0.0001	0.10	0.0002
Rank 11	2	0.0002	0.10	0.0001	0.25	0.0000
Rank 12	1	0.0002	0.09	0.0001	0.06	0.0001
Rank13	1	0.0001	0.07	0.0000	0.29	0.0084
HHI		3014		2420		2890
Merge 4 &5						
New HHI		3080		2585		3040
Change HHI		65		165*		150**
Merge 1 & 7						
New HHI		3234		2460		2982
Change HHI		220		40*		92**