Is the Consumer Sector Competitive in the U.K.? A Test Using Household-Level Demand Elasticities and Firm-Level Price Equations

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This article tests the hypothesis of perfect competition in the consumer nondurables sector of the U.K. economy. First, it uses household-level data to estimate time-varying price elasticities of demand for disaggregated commodity groups. U.S. product prices are used as instruments for U.K. prices in the demand equation. Then it matches the product definitions to the Standard Industry Classification and uses firm-level data, combined with the estimated elasticities, to estimate a price model of firms operating in different industries. Household characteristics are used as instruments for the demand effects in the firms' supply equation. The results reject perfect competition and appear to be consistent with the argument that less competition increases profits through collusion.

KEY WORDS: Competition; Consumer behavior; Demographics; Identification; Profitability.

1. INTRODUCTION

Economists have always been concerned with the degree of competition that takes place in the markets. The traditional approach to measure competition, the so-called "structure-conduct-performance" (SCP) paradigm, has focused on the relationship between measures of market power, such as market shares and industrial concentration, and measures of performance, such as price–cost margins, across different sectors of the economy. The positive relationship between both groups of measures, uncovered in many empirical studies of this line, is interpreted as evidence that firms are using their market power to increase profits through noncompetitive behavior (see Schmalensee 1989 for a survey).

More recently, a new string of the literature has emerged, the New Empirical Industrial Organization (NEIO), which criticizes the traditional approach on both empirical and theoretical grounds. The empirical criticism focuses on the simultaneous determination of market structure and economic performance that could lead economists to infer collusion where there is none. Theoretically, the NEIO studies emphasize the absence of structural models driving the SCP estimation procedures and the fact that firms in different industries could have different forms of competition. The NEIO studies focus instead on firms producing differentiated products in a single industry, where demand information is used, together with a model of firm conduct, to recover markups and marginal costs (see Bresnahan 1989 for a survey and Berry, Levinsohn, and Pakes 1995 for an influential application).

This article is an attempt to bridge these two approaches. It estimates firm-level pricing equations in the consumer nondurables sector in the U.K. to test the hypothesis of perfect competition among the firms that operate in this sector. Like the NEIO studies, it estimates household-level demand elasticities using micro data, but unlike these studies, it models the demand for several goods instead of modeling different brands of just one good, which gives a broader picture than the single-industry studies.

On the supply side, the article models the behavior of firms operating in different industries and predicts that their profitability will depend on their market shares, the distribution of their sales across industries, a conduct parameter, and the price elasticities of demand. Because we actually observe the firm's markups (from their balance sheet data), we can estimate price equations using firm-level data and price elasticities to evaluate various theories of competition. This is an important contrast to the NEIO approach, which must impose a specific form of market conduct to recover the markup estimates using the estimated demand elasticities. We also use the demand information to shed light on a traditional debate about whether the positive relationship between market share and profitability reflects noncompetitive behavior or differential efficiency (see Slade 2004).

The combination of various independent micro datasets allows this study (unlike previous SCP studies) to identify both the demand and the supply equations and thus to deal explicitly with the endogeneity problem. In the demand equation, U.S. prices are used to capture changes in worldwide marginal costs that can identify the U.K. price effects. Moreover, the detailed information on household characteristics, available in the consumer surveys, are used as instruments that shift demand independently of the firms' pricing behavior, which identifies the supply equation.

The article is organized as follows. Sections 2 and 3 present the supply and demand models. Section 4 estimates the demand model, and Section 5 describes the matching process between supply and demand. Section 6 estimates the supply model, and Section 7 concludes.

2. MODELING SUPPLY

In the supply setup, firms can operate in more than one industry. Consider the case of a firm f operating in industries i and j with costs functions c_i and c_j, choosing quantities q_i and q_j to maximize total profits, π_f,

$$\max_{q_i, q_j} \pi_f = p_i q_i + p_j q_j - c_i(q_i) - c_j(q_j). \tag{1}$$

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The first order conditions for profit maximization are

$$\left.\frac{\partial \pi_f}{\partial q_i}\right|_{q_j} = \frac{\partial p_i}{\partial Q_i}\frac{\partial Q_i}{\partial q_i}q_i + p_i + \frac{\partial p_j}{\partial Q_i}\frac{\partial Q_i}{\partial q_i}q_j - \frac{\partial c_i}{\partial q_i} = 0 \tag{2}$$

and

$$\left.\frac{\partial \pi_f}{\partial q_j}\right|_{q_i} = \frac{\partial p_j}{\partial Q_j}\frac{\partial Q_j}{\partial q_j}q_j + p_j + \frac{\partial p_i}{\partial Q_j}\frac{\partial Q_j}{\partial q_j}q_i - \frac{\partial c_j}{\partial q_j} = 0 \tag{3}$$

with $Q_i = \sum_i q_i$ and $Q_j = \sum_j q_j$.

The markup in each industry, under constant returns to scale, is

$$\frac{p_i - c_i{}'}{p_i} = \frac{\pi_i}{r_i} = -\frac{MS_i\theta_i}{\varepsilon_{ii}} - \frac{1}{\varepsilon_{ij}}\frac{r_j}{R_i}\theta_i \tag{4}$$

and

$$\frac{p_j - c_j{}'}{p_j} = \frac{\pi_j}{r_j} = -\frac{MS_j\theta_j}{\varepsilon_{jj}} - \frac{1}{\varepsilon_{ij}}\frac{r_i}{R_j}\theta_j. \tag{5}$$

Hence the firm's markup over its marginal cost ($c_i' = \frac{\partial c_i}{\partial q_i}$) in industry i, for example, is a function of its market share ($MS_i = \frac{q_i}{Q_i}$), its sales in industry j ($r_j = p_j q_j$), total sales in industry i ($R_i = p_i Q_i$), the own-price and cross-price elasticities of demand ($\varepsilon_{ii} = \frac{\partial Q_i}{\partial p_i}\frac{p_i}{Q_i}$, $\varepsilon_{ij} = \frac{\partial Q_i}{\partial p_j}\frac{p_j}{Q_i}$), and the conduct parameter ($\theta_i = \frac{\partial Q_i}{\partial q_i}$). The conduct parameter reflects how the firm expects the other firms in the industry to react to an output expansion or contraction (see Bresnahan 1989). Therefore, if $\theta_i = 0$, then price equals marginal cost (perfect competition), whereas $\theta_i = 1$ implies Cournot behavior, for example.

To assess a firm's overall profitability, we use the fact that

$$\left(\frac{\pi}{r}\right)_f = \frac{\pi_i + \pi_j}{r_i + r_j} = \frac{\pi_i}{r_i}\frac{r_i}{(r_i + r_j)} + \frac{\pi_j}{r_j}\frac{r_j}{(r_i + r_j)}, \tag{6}$$

so that

$$\left(\frac{\pi}{r}\right)_f = \left[-\frac{MS_i\theta_i}{\varepsilon_{ii}}\frac{r_i}{(r_i + r_j)} - \frac{\theta_i}{\varepsilon_{ij}}\frac{r_j}{R_i}\frac{r_i}{(r_i + r_j)}\right] + \frac{\pi_j}{r_j}\frac{r_j}{(r_i + r_j)}. \tag{7}$$

Therefore,

$$\left(\frac{\pi}{r}\right)_f = \left[-\frac{MS_i\theta_i}{\varepsilon_{ii}}w_i - \frac{MS_i\theta_i}{\varepsilon_{ij}}w_j\right] + \frac{\pi_j}{r_j}\frac{r_j}{(r_i + r_j)}, \tag{8}$$

where $w_i = \frac{r_i}{(r_i + r_j)}$ is the share of the firm's revenues out of industry i. Hence the final expression for the firm's overall profitability is

$$\left(\frac{\pi}{r}\right)_f = \theta_i\left[MS_i\left(-\frac{w_i}{\varepsilon_{ii}} - \frac{w_j}{\varepsilon_{ij}}\right)\right] + \theta_j\left[MS_j\left(-\frac{w_j}{\varepsilon_{jj}} - \frac{w_i}{\varepsilon_{ij}}\right)\right]. \tag{9}$$

This is the expression that will be taken to the data after the demand estimation.

It is important to point out that the demand elasticities vary only across industries, which makes this study quite different from the usual NEIO studies, where brand-level elasticities are calculated. In our setup, differences in markups across firms in the same sector stem from differences in their market shares, determined by their marginal costs, due to differences in their production technology.

3. MODELING DEMAND

3.1 The Almost-Ideal Model

On the demand side, it is assumed that intertemporal and intratemporal weak separability holds, and the expenditure decision is modeled as a three-stage budgeting decision. First, the household decides between spending on nondurable goods on the one hand and saving and buying durable and other goods on the other hand. Given that preferences are weakly separable over time, once the optimal saving decision is made, prices and incomes outside the period have no independent effect on within-period allocations. In the second stage, the household decides the amount to spend on each of the four nondurable groups considered here: food, alcohol, clothing, and other nondurables. Finally, in the third stage the household makes the decision on how much to spend on each of the goods within the broad groups. This article estimates the parameters of the third-stage decision. The separability assumption means that the decision on the ranking of commodities in any one of the groups is independent of expenditures and prices of the goods outside that group.

Let m_t be the expenditure allocated by a household to nondurable goods in period t. Given m_t, the household decides (based also on preferences and within-period group prices) how to spend it on food (x_t^f), alcohol (x_t^a), clothing (x_t^c), and other nondurables (x_t^o). Given each group expenditure x_t^g, the household then decides how much to spend on each individual good ($p_{it}q_{it}$), according to the following share equation (almost-ideal model proposed by Deaton and Muellbauer 1980, with time subscripts omitted):

$$w_i = \alpha_i + \sum_{j=1}^{n_g}\gamma_{ij}p_j + \beta_i \log(x^g/P), \tag{10}$$

where $w_i = p_i q_i / x^g$, P is a relevant price index, α_i and γ_{ij} and β_i are parameters to be estimated, and p_j's are the intragroup prices. The parameter α_i is allowed to include a series of household characteristics (z_k), seasonals (S), and time trends (T),

$$\alpha_i = \alpha_0 + \sum_k \alpha_{ik}z_k + \delta T + \vartheta S, \tag{11}$$

and the within-group Stone price index is used as an approximation,

$$\ln(P) = \sum_{j=1}^{n_g} w_j \ln(p_j), \tag{12}$$

where w_j is the monthly average share of good j in the dataset.

The budget elasticity is equal to

$$\varepsilon_b = \frac{\beta_i}{w_i} + 1, \tag{13}$$

whereas the uncompensated and compensated price elasticities are

$$\varepsilon_{ij}^u = \frac{\gamma_{ij}}{w_i} - \beta_i\frac{w_j}{w_i} - \delta_{ij} \tag{14}$$

and

$$\varepsilon_{ij}^c = \frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij}, \tag{15}$$

where δ_{ij} is the Kronecker delta.

3.2 Demand Identification

Estimation of demand and supply equations is the classic example of endogeneity (see Working 1927), because prices and quantities are simultaneously determined. Consider the share equation defined earlier, with an stochastic component

$$\frac{p_i q_i}{x^g} = \alpha_i + \sum_{j=1}^{n_g} \gamma_{ij} p_j + \beta_i \log(x^g/P) + u_i. \qquad (16)$$

If price variation is driven by product-specific demand shocks (conditionally on demographics, seasonal variations, and time trends), then one would expect the ordinary least squares estimator of the γ_{ij} to be inconsistent. Moreover, the presence of p_i in both sides of the almost-ideal equation could exacerbate this problem. This would be the case in, for example, the case of product differentiation, which has been neglected so far in this article.

This article deals with simultaneity in two ways. First, it uses individual consumer micro data, which "permits the observable variation between consumers to trace out much of the demand curve for products" (Bresnahan 1998; see also Goldberg 1995). More important, it uses information on U.S. retail prices of the products (defined in the same level of aggregation as in the U.K.) as instruments for the U.K. product prices. The identification assumption is that the U.K. demand for U.S. products is too small a share of the world demand to influence U.S. prices, or that international correlation of demand shocks is negligible, so that movements in U.S. prices mainly reflect changes in worldwide costs and the U.S. demand. Hausman (1996) and Nevo (2001) studied the U.S. ready-to-eat cereal market and used brand prices in other U.S. cities as instruments for the price in a particular city, under the assumption that demand shocks are independent across cities. The assumption used in this article is much weaker and, if valid, means that the share equations are identified.

Figure 1 shows that the behavior of the 12th differences of the December U.S. retail prices of four of our products is similar to that of their U.K. counterparts, which is a necessary (although not sufficient) condition for identification. The U.K. retail price series is taken from the Central Statistical Office's (CSO) "Retail Price Index" publication, and the U.S. retail price series is taken from the Bureau of Labor Statistics website; the figures for the other products are available from the author on request. Table A.4 in the Appendix describes the matching between the U.S. and the U.K. product definitions and shows that the matching is pretty reasonable.

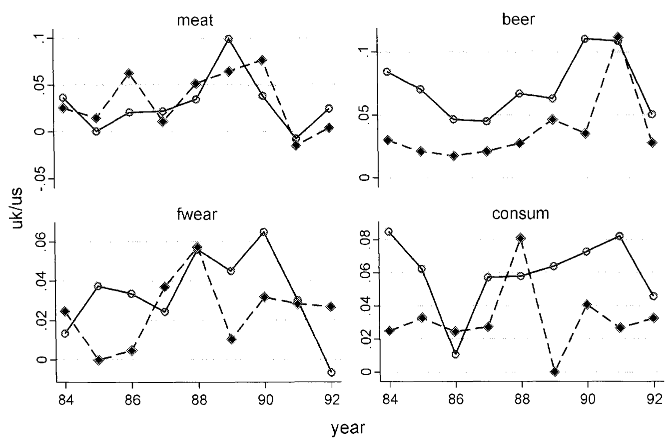

Figure 1. U.K. (——o——) and U.S. (– –◆– –) Retail Prices.

4. DEMAND ESTIMATION

The framework developed here in departs from other demand studies that use micro data (see Blundell, Pashardes, and Weber, 1993) in that the products are defined at a more disaggregated level, so as to match the three-digit Standard Industry Classification (SIC) definition on the supply side. Moreover, the focus is on time-varying elasticities, which is used in first-differenced form when combining demand and supply information in the next section.

The estimation of the four demand systems is carried out using the two-stage procedure outlined by Browning and Meghir (1991). In the first stage, each equation in each system is estimated by an instrumental variables (IV) technique, with total group expenditures treated as endogenous and total income, real interest rates, and the lagged unemployment rate used as instruments (following our three-stage budgeting approach). This procedure allows for measurement errors in expenditures and shares, which, by assumption, is the reason for the 0's recorded in the third stage. It also takes care of a division bias associated with the log expenditure term.

Given the first-step estimates, we impose the symmetry cross-equation restrictions by means of a minimum distance estimator (see Rothenberg 1973). Let $\mathbf{s}$ denote the unrestricted parameters and $\mathbf{s}^*$ denote their restricted counterparts. The restrictions can then be expressed as

$$\mathbf{s} = R\mathbf{s}^*. \qquad (17)$$

To impose these restrictions, we choose $\mathbf{s}^*$ so as to minimize

$$m = (\hat{\mathbf{s}} - R\mathbf{s}^*)\widehat{\mathbf{w}}^{-1}(\hat{\mathbf{s}} - R\mathbf{s}^*), \qquad (18)$$

where $\hat{\mathbf{s}}$ is a consistent estimator of $\mathbf{s}$ and $\widehat{\mathbf{w}}$ is an estimate of its variance–covariance matrix. This procedure also takes into account the cross-equation correlations in the error term.

4.1 Data

The data used on the demand side come from the U.K. Family Expenditure Surveys (FES) from 1978 to 1992. This survey has been widely used by studies investigating the properties of household consumption, savings, and earnings (see, e.g., Attanasio and Browning 1995). It contains information on household expenditures on a detailed set of goods (recorded in a 2-week diary) and also on household composition. A list of the variables used and some descriptive statistics are presented in Tables A.2 and A.3 in the Appendix.

The goods modeled here are cereal, bread/biscuits, meat, fish, oils/fats, milk, soft drinks, sugar, sweets/chocolates, and fruits/vegetables in the food group. In the alcohol group, the focus is on beer, wine, and spirits. The goods modeled in the clothing group are general clothing and footwear. Finally, the other nondurables group comprises household consumables, books/newspapers, and toys/sporting goods. The goods were defined so as to match the industry definition given by the

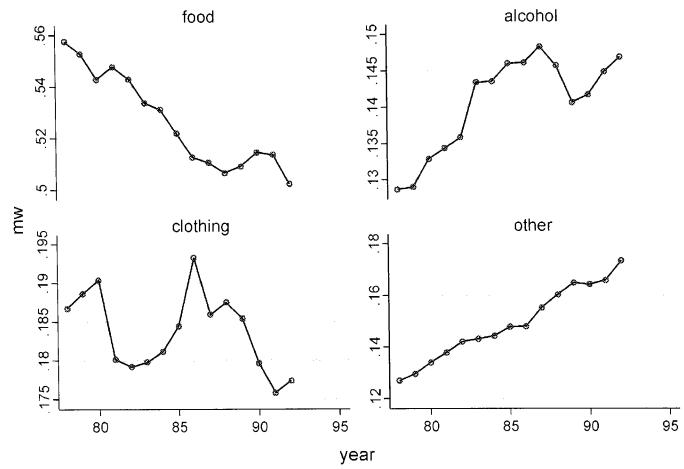

Figure 2. Shares of Nondurable Expenditures Over Time.

U.K. SIC for 1980. When a higher level of aggregation in the product definition than that provided in the FES was needed, expenditures on the disaggregated goods were added, and the price was computed as a weighted average of each good's price, with weights given by the FES (reflecting the importance of the good for a representative U.K. consumer). The principal excluded goods were durables, vehicles, and housing, to avoid the difficulties involved in modeling the dynamics involved in the household's decision to buy these goods.

Figure 2 shows the behavior of the expenditures in each group as shares of total nondurables expenditures over time. It appears that expenditures in alcohol and other nondurables have increased substantially over the last 14 years. It also seems that, as expected, the food expenditure share has decreased markedly over the 1980s, whereas the clothing expenditure share demonstrated a great deal of fluctuation in the period.

4.2 Results

Table 1 reports the own-price elasticities of the food system evaluated at mean predicted shares for each product over the whole sample period. Each row shows the results of a particular share regression. Column (1) includes only the group prices, seasonals, and the (instrumented) total group expenditures. Some own-price elasticities, like those of meat, cereal, and soft drinks, are estimated to be positive, which is unlikely to be the case unless these are Giffen goods. The inclusion of household composition and demographic variables in column (2) causes major changes in the elasticities, which emphasizes the importance of working with micro data and controlling for observed household heterogeneity. Column (3) uses the U.S. prices as instruments for the U.K. prices, as discussed earlier. This has the effect of raising the absolute value of most of the estimated elasticities, although the changes are not dramatic. Our interpretation of this result is that using micro data provided us with sufficient variation in the data to identify the demand curve, so that the we are not able to reject the exogeneity of U.K. prices in this case.

Table 1 also presents the compensated price and the budget elasticities, using the coefficients estimated in column (3). The compensated own-price elasticities are all negative, as the theory predicts, and are significantly different from 0 at conventional levels. The estimated budget elasticities also make sense, showing that bread, milk, and cereals are necessities; fruits/vegetables, meat, fish, soft drinks, and sweets are luxuries; and oils/fats and sugar are inferior goods. Finally, the overidentification test performs quite well for a chi-squared distribution with 15 degrees of freedom.

Table 2 presents the results of the alcohol, clothing, and other nondurable goods demand systems. The results for the different specifications are qualitatively very similar to those for the

Table 1. Estimated Elasticities: Food

	Price uncompensated					
Product	*(1)*	*(2)*	*(3)*	*Price compensated*	*Budget*	*Over ID $\chi_2(15)$*
Fruits and vegetables	−.239	−.595	−.752	−.416	1.507	74
	.026	*.037*	*.058*	*.061*	*.026*	
Bread	−.668	−.446	−.590	−.518	.459	44
	.143	*.156*	*.219*	*.219*	*.028*	
Meat	.119	−1.063	−1.274	−1.011	1.189	50
	.038	*.096*	*.114*	*.113*	*.030*	
Fish	−.897	−1.104	−1.209	−1.127	1.919	4
	.074	*.181*	*.214*	*.214*	*.069*	
Oils and fats	−.354	−.239	−.168	−.178	−.425	24
	.051	*.068*	*.078*	*.077*	*.068*	
Milk	−1.125	−.478	−.534	−.390	.729	19
	.080	*.103*	*.133*	*.132*	*.026*	
Soft drinks	.129	−.418	−.569	−.528	1.240	42
	.156	*.191*	*.248*	*.248*	*.075*	
Sugar	−.624	−.535	−.517	−.529	−.488	27
	.186	*.200*	*.249*	*.249*	*.071*	
Sweets	−1.651	−.644	−.445	−.378	1.574	133
	.132	*.265*	*.366*	*.366*	*.080*	
Cereal	.691	.135	−.531	−.514	.523	23
	.143	*.156*	*.800*	*.800*	*.064*	
Sample size	105,042	105,042	105,042			

NOTE: IV estimates. Standard errors are in italics. Controls in column (1) are ln(expenditure), seasonal dummies, and the other group prices. Controls in columns (2) and (3) are those in column (1) plus 10 regional, 15 demographic, and 4 occupational variables and time trends. Instruments for ln(expenditure) are ln(income), change in real interest rates, lagged unemployment rate, and year dummies. U.S. product prices are used as additional instruments in column (3).

Table 2. Estimated Elasticities: Alcohol, Clothing, and Other

Product	*Price uncompensated (1)*	*(2)*	*(3)*	*Price compensated*	*Budget*	*Over ID* $\chi_2(15)$
Beer	−.731	−.653	−.894	−.605	.494	32
	.034	*.151*	*.228*	*.229*	*.016*	
Wine	−1.647	−.990	−1.051	−.683	2.024	24
	.052	*.177*	*.190*	*.191*	*.042*	
Spirits	.407	−.544	−.630	−.606	1.477	23
	.194	*.360*	*.229*	*.594*	*.027*	
Sample size	75,796	75,796	75,796			
Clothing	−1.138	−1.070	−1.074	−.241	1.024	18
	.187	*.057*	*.028*	*.062*	*.006*	
Footwear	−1.030	−1.197	−1.215	−1.048	.891	18
	.042	*.247*	*.269*	*.270*	*.027*	
Sample size	79,228	79,228	79,228			
Consumables	.009	−.665	−.593	−.252	.782	88
	.071	*.095*	*.111*	*.111*	*.013*	
Books	−.965	−.697	−.716	−.259	1.025	45
	.023	*.053*	*.059*	*.059*	*.013*	
Toys and sporting goods	.208	−.775	−.630	−.428	1.706	40
	.059	*.212*	*.229*	*.228*	*.035*	
Sample size	104,158	104,158	104,158			

NOTE: IV estimates. Standard errors are in italics. Controls in column (1) are ln(expenditure), seasonal dummies, plus the other group prices. Controls in columns (2) and (3) are those in column (1) plus 10 regional, 15 demographic, and 4 occupational variables and time trends. Instruments for ln(expenditure) are ln(income), change in real interest rates, lagged unemployment rates, and year dummies. U.S. product prices are used as additional instruments in column (3).

food system. The inclusion of household demographic variables has the effect of reversing the positive elasticities estimated in the first column for spirits, household consumables, and toys/sporting goods. Using U.S. prices as IVs also has the effect of raising the absolute value of the estimated elasticities, especially in the alcohol system. Again, all own-price compensated elasticities are negative, and the budget elasticities show that, for example, wine, spirits, books, and toys/sporting goods are luxuries relative to the other goods in their system. The overidentification tests again perform quite well in most cases, suggesting that the instruments are valid.

5. MATCHING SUPPLY AND DEMAND

5.1 The Matching Process

Table A.4 in the Appendix sets out the matching process. The first column presents the SIC definitions, and the second column gives the U.K. product definitions. The third column gives the U.S. product definitions, whose prices were used as IVs in the previous demand estimation. One can see that the matching is pretty good, so we are confident in interpreting the results that follow as providing evidence of the impact of consumer demand for each product on the performance of the firms that produce it.

To confirm the validity of the matching process, Figure 3 compares the behavior of the 12th differences of each year December producer prices vis-a-vis the retail prices in the U.K. for four of our products. The U.K. producer price series is taken from British Business until 1983 and subsequently from the Business Monitor M22, and the U.K. retail price series is taken from the CSO's "Retail Price Index"; the figures for the other products are available from the author on request. The figure shows that the producer and the retail prices move close together, confirming that the matching process is satisfactory. The figure also shows that other possible determinants of the retail prices, such as retailers' markups, have remained stable over the sample period. Differences in retailers' margins across sectors are captured in the firm fixed effects.

6. SUPPLY ESTIMATION

6.1 Supply Identification

Having estimated the demand side, we now must deal with identification of the supply equation. Consider the markup equation (9) and assume that the conduct parameter is the same for all firms in the consumer sector of the economy, conditional on firm-specific effects and random shocks. We then have, under constant returns to scale, the supply equation that will be

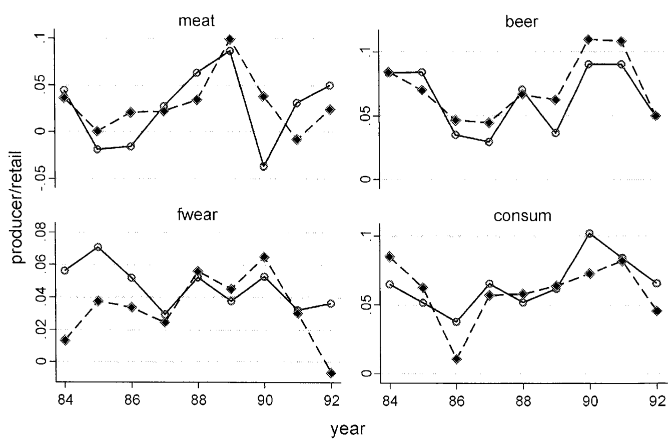

Figure 3. U.K. Retail (— —◆— —) and Producer (——o——) Prices.

taken to the data,

$$\frac{\pi_f}{r_f} = \alpha_f + \theta\left[MS_i\left(-\frac{w_i}{\varepsilon_{ii}} - \frac{w_j}{\varepsilon_{ij}}\right) + MS_j\left(-\frac{w_j}{\varepsilon_{jj}} - \frac{w_i}{\varepsilon_{ij}}\right)\right] + u_f. \quad (19)$$

Shocks to the firms' prices u_f will affect both the firms' profitability (directly) and the product market elasticity (through its retail price), although the direction of the bias is not clear a priori. Positive product price shocks tend to increase the markup, but will increase the absolute value of ε_{iit} only if the product demand is price-inelastic. Given that 13 of the 18 products in Tables 1 and 2 have inelastic demands on average, one can tentatively predict that the ordinary least squares estimate of θ will be downward biased (in absolute value). One could then ask why the producers do not increase prices in the face of an inelastic product demand. But of course the elasticity facing an individual producer also depends on the behavior of its competitors.

This bias can be eliminated by using only the variation in demand elasticities that comes from exogenous factors. One of the advantages of the procedure used in this article is that household characteristics, available from the survey data, provide a unique way to identify the supply equation. The fitted values of the almost-ideal equation estimated earlier are

$$\widehat{w_{it}} = \widehat{\alpha_{it}} + \sum_j \widehat{\gamma}_{ij}\log(p_{ijt}) + \widehat{\beta}_i \log\left(\frac{x_{it}}{P_t}\right) \quad (20)$$

and

$$\widehat{\alpha_{it}} = \widehat{\alpha_0} + \sum_i \widehat{\alpha_i} z_{it} + \widehat{\delta} T + \widehat{\vartheta} S, \quad (21)$$

so that the price elasticities were computed according to

$$\varepsilon_{it} = \frac{\widehat{\gamma_{ii}}}{\widehat{w_{it}}} - \widehat{\beta_i} - 1, \quad (22)$$

where $\widehat{w}_{it}$ are the predicted shares. The household characteristics (z_{it}), seasonals (S), and time trends (T) enter the share equations to reflect differences in household preferences and composition and are exogenous to the firm's supply equation. Therefore, to identify the supply equation we use only the variation in the shares that comes from these exogenous factors (because the firm-level information is available only annually, the seasonal factors cancel out and are not used in the estimation procedure),

$$\varepsilon^e_{it} = \frac{\widehat{\gamma_{ii}}}{\widehat{w^e_{it}}} - \widehat{\beta_i} - 1, \quad (23)$$

where

$$\widehat{w^e_{it}} = \widehat{\alpha_0} + \sum_i \widehat{\alpha_i} z_{it} + \widehat{\delta} T. \quad (24)$$

The variables used to predict the exogenous variation in the shares are age; age squared; number of adults; number of adults squared; number of females; a single-parent dummy; number of kids in various age groups; five occupational dummies; dummies for retired, self-employed, and unemployed heads; and time trends. There is no reason to expect that these variables affect the firms' pricing behavior, conditional on their effect

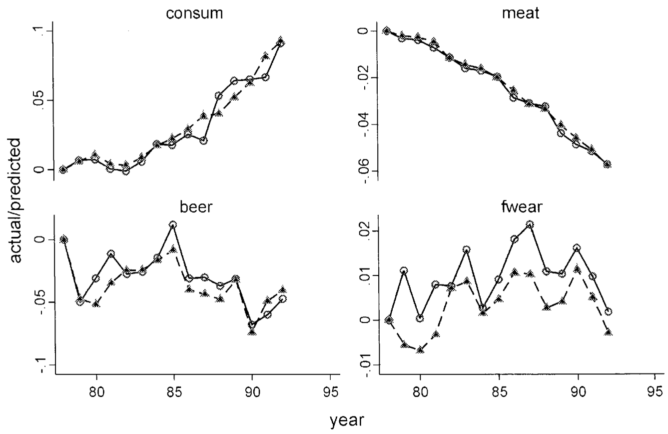

Figure 4. Actual (——o——) and Predicted (— —◆— —) Shares.

on the elasticities. Moreover, these variables impact the share equations differently, providing cross-section and time series variation in the exogenous elasticities.

To provide further insight into the nature of our instrumenting strategy, Figures 4–6 describe the behavior of the predicted shares of four of our goods over time. First, Figure 4 shows that the demand model can predict the actual behavior of the expenditure share of each product quite well. The fit is worst in the case of footwear, which may be related to the fact that footwear and clothing are more durable than the other products, so that dynamic considerations might be important for the demand of these goods. The figures for the other products are available from the author on request. Figure 5 compares the behavior of the predicted shares using all variables with the shares computed using only the exogenous variables and shows that they can be very different, depending on the product. Figure 6 translates the differences in the shares into differences in elasticities, using expression (23). The differences between the predicted and the "exogenous" elasticities are similar to the differences in the shares, but they also depend on the sign and magnitude of the estimated price coefficient, as is clear in (23).

Because market shares are also likely to be correlated to the disturbances in (19), this article uses a system generalized method-of-moments (GMM) estimator, with lagged values of market share used as IVs. The estimator combines a set

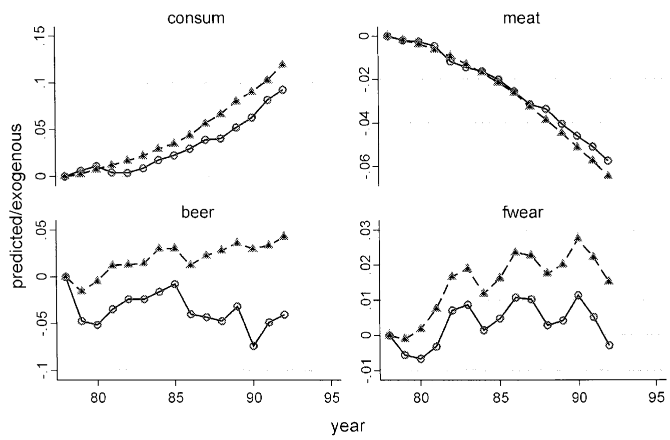

Figure 5. Predicted (——o——) and Exogenous (— —◆— —) Shares.

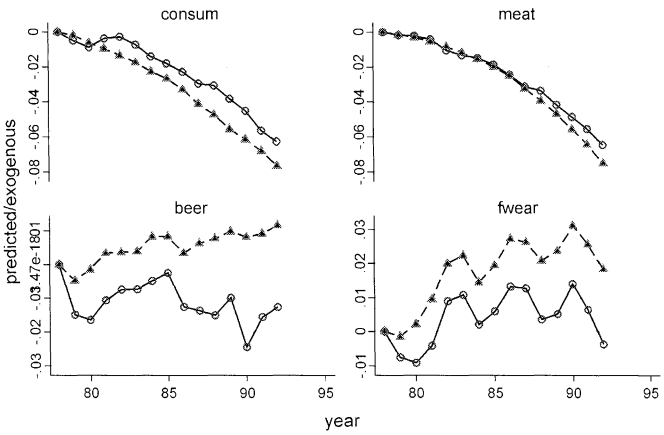

Figure 6. Predicted (—o—) and Exogenous (– –◆– –) Elasticities.

of moment restrictions relating to the equations in first differences with a set of moment restrictions relating to the equation in levels in an efficient way (see Blundell and Bond 1998). Lagged levels of market share are used as instruments in the first-differences specification, and lagged differences of market share are instruments in the levels specification. The contemporaneous values of the demand elasticities are instrumenting themselves in all specifications, because we compare the coefficients obtained when different sources of variation are used to compute these elasticities.

6.2 Data

To estimate (19), we use data on company accounts available from the U.K. Datastream on-line service. The industry-level information comes from the U.K. Census of Production (COP). The criteria for selecting firms was that they operated in the consumer nondurables sector of the economy and that information was available both on the distribution of sales across different industries and on the percentage of sales sold abroad. We were left with an unbalanced sample of 161 firms operating from 1978 to 1992.

The dependent variable used throughout this study is accounting pretax profits (before depreciation allowances) divided by total sales. (For a comparison between this measure and Tobin's q, see Stevens 1990.) The market share variable traditionally used in SCP studies is the ratio of firm's total sales to its main industry sales. However, many firms are diversified and operate across different industries. The first step toward improving the market share variable is to use only the firm's *domestic* sales in the numerator and exclude industry exports from the total industry sales in the denominator, to concentrate on the relationship between the firm's domestic market share and its profitability. The second step is to use the sales distribution information to compute a market share in each industry in which the firm operates and apply the theoretical model developed earlier to incorporate this information into the estimation procedure. Finally, the industry-level variables used in this study are the five-firm concentration ratio and import protection [(1 − imports)/sales]. Table A.1 in the Appendix presents some descriptive statistics of the firm- and industry-level variables used in this article.

6.3 Results

In this section we use the estimated time-varying uncompensated demand elasticities, together with the market shares, to test for perfect competition in the U.K. consumer nondurables sector. Table 3 presents the main results, with all models estimated in first differences to eliminate the firms' fixed effects. In column (1) we estimate equation (19), using all of the variation in the demand elasticities but only the information from the main industry in which the firm operates. The estimated coefficient is positive but imprecisely estimated, which means that we cannot reject perfect competition in this specification. However, the serial correlation test at the bottom of the table clearly rejects the null, and it is well known that serial correlation invalidates the use of lags as instruments (see Arellano and Bond 1991).

Therefore, column (2) includes a lagged dependent variable, which attracts a positive and highly significant coefficient. The coefficient on market share divided by elasticity is reduced by half but is now significantly different from 0 at conventional levels, and now the serial correlation test cannot reject the null. Column (3) uses only the exogenous variation in the shares to compute the demand elasticities, and the estimated coefficient is now two times higher and very precisely estimated. This shows that the spurious correlation, caused by the presence of prices both in the elasticities and in the markups, was biasing the estimated coefficient downward.

Column (4) includes the information on the cross-price elasticities; that is, it takes explicitly into account the fact that firms operate in different industries, as in (19). Interestingly, the magnitude of the estimated coefficient declines, indicating that the prices charged by the firms are actually more competitive than was implied by the specification that ignored the substitutability between goods. This result was expected, because the potential for price increases is higher when the negative demand effects are partially compensated for by the increase in demand for the other products that the firm produces. Therefore, a markup that was considered noncompetitive earlier turns out to be more competitive when substitutability is taken into account.

Table 3. Testing for Perfect Competition

$(\Delta \frac{\pi}{r})$	(1)	(2)	(3)	(4)
$(\Delta \frac{MS}{\varepsilon})_{it}$	.129	.066	.120	.087
	.137	*.030*	*.044*	*.029*
$(\Delta \frac{\pi}{r})_{it-1}$		.907	.903	.907
		.070	*.067*	*.066*
Time dummies	Yes	Yes	Yes	Yes
Over ID (df)	79 (62)	94 (86)	106 (86)	104 (86)
p value	.064	.252	.070	.080
Serial correlation	−2.097	−1.557	−1.566	−1.561
p value	.036	.120	.117	.119
Sample size	1,551	1,551	1,551	1,551

NOTE: Standard errors (robust to heteroscedasticity) are in italics. Column (3) uses only the exogenous variation in own-price and cross-price elasticities. Column (4) incorporates the cross-price elasticities. All models are estimated by system-GMM. Instruments for the differenced equations are MS_{it-2}, η_{it}, and $\frac{MS_{it-2}}{\eta_{it}}$ in column (1) and plus $(\frac{\pi}{r})_{it-2}$ in columns (2), (3), and (4). Instruments for the level equations are ΔMS_{it-1} and $\Delta \eta_{it}$ in column (1) and $\Delta \frac{\pi}{r}{}_{it-1}$ in columns (2), (3), and (4). Serial correlation is a test for second-order serial correlation in the first-differenced residuals, asymptotically distributed as N(0, 1) under the null. Over ID is a test of overidentifying restrictions, asymptotically distributed as chi-squared under the null of instrument validity.

6.4 Market Power of Differential Efficiency?

Economists have long debated whether the impact of market structure variables on profitability reflects "tacit collusion" or "differential efficiency." The fact that demand elasticities have been estimated can shed more light on this issue from a different viewpoint. Even the most collusive group of firms will not be able to increase prices and profits in the face of a very elastic demand. Therefore, to examine whether industry concentration and import protection facilitate collusion, one must take into account that demand elasticities may vary across sectors in a way that may be correlated with concentration and import protection.

Suppose, for example, that the conduct parameter is a function of concentration and import protection,

$$\theta_i = \alpha_0 + \alpha_1 \operatorname{Im} p_i + \alpha_2 Conc_i.$$

Substituting this expression into (19) (ignoring the cross-price effects for simplicity), one gets

$$\frac{\pi_i}{r_i} = \alpha_i + \alpha_0 \frac{MS_i}{\varepsilon_{ii}} + \alpha_1 \frac{MS_i * \operatorname{Im} p_j}{\varepsilon_{ii}} + \alpha_2 \frac{MS_i * Conc_j}{\varepsilon_{ii}} + u_i. \tag{25}$$

If the impact of market shares on profitability is higher in more concentrated and protected industries, after demand elasticities have been taken into account, this will provide evidence that firms are colluding to increase prices (the "market power" effect), because high concentration and import protection facilitate collusion. If this is not the case, however, then the correlation between market share and profitability probably reflects the fact that more-efficient firms have higher market shares *and* are more profitable.

Table 4 provides the results. Column (1) repeats the last column of Table 3 for comparison. Column (2) includes the interaction between concentration and market share (divided by the elasticities) in the equation, which attracts a positive, but not significant, coefficient. Column (3) includes import protection instead of concentration, with a similar result. Column (4) includes both variables simultaneously; the magnitude of their estimated coefficients increases substantially, so that the concentration coefficient becomes significantly different from 0 with a p value of .07, and import protection is now significant with a p value of .03. Moreover, the market share coefficient is now negative. These results imply that a high market share alone is not sufficient to increase profitability, so that the impact of market share on profitability increases with concentration and import protection.

Table 4. Market Power or Differential Efficiency?

$(\Delta\frac{\pi}{r})_{it}$	(1)	(2)	(3)	(4)
$(\frac{MS}{\varepsilon})_{it}$	.087	−.021	.015	−.756
	.029	*.149*	*.115*	*.476*
$(\frac{Conc*MS}{\varepsilon})_{it}$		.188		.541
		.225		*.387*
$(\frac{\text{Im}p*MS}{\varepsilon})_{it}$			.147	.643
			.159	*.312*
$(\Delta\frac{\pi}{r})_{it-1}$	.907	.878	.856	.863
	.066	*.051*	*.057*	*.051*
Time dummies	Yes	Yes	Yes	Yes
Over ID (df)	104 (86)	147 (166)	146 (166)	147 (202)
p value	.080	.852	.863	.9985
Serial correlation	−1.561	−1.579	−1.562	−1.564
p value	.119	.114	.118	.118
Sample size	1,551	1,551	1,551	1,551

NOTE: Standard errors (robust to heteroscedasticity) are in italics. All models are estimated by system-GMM. Instruments for the differenced equations are MS_{it-2}, $Conc_{t-2}$, $\text{Im}p_{t-2}\eta_{it}$, $\frac{MS_{it-2}}{\eta_{it}}$, $\frac{Conc_{it-2}}{\eta_{it}}$, $\frac{\text{Im}p_{it-2}}{\eta_{it}}$, and $(\frac{\pi}{r})_{it-2}$. Instruments for the levels equations are ΔMS_{it-1}, $\Delta Conc_{it-1}$, $\Delta \text{Im}p_{it-1}$, $\Delta\eta_{it}$, and $\Delta\frac{\pi}{r}{}_{it-1}$. Serial correlation is a test for second-order serial correlation in the first-differenced residuals, asymptotically distributed as N(0, 1) under the null. Over ID is a test of overidentifying restrictions, asymptotically distributed as chi-squared under the null of instrument validity.

7. CONCLUSIONS

This article has tested the hypothesis of perfect competition in consumer nondurables sector of the U.K. economy. A model of firm behavior was constructed, and two independent datasets, one with firm- and industry-level data and the other with information on household characteristics and expenditures, were used to investigate whether firms behave in a noncompetitive manner.

The parameters of almost-ideal demand systems for four groups of goods (food, alcohol, clothing, and other nondurables) were estimated using time series of cross-sectional household data. Product prices in the U.S. were used as instruments for product prices in the U.K. The resulting budget and price elasticities accorded with demand theory and showed intuitive patterns. In particular, time-varying uncompensated price elasticities were computed that showed substantial cross-sectional and time series variation.

The very detailed product definitions in the U.K. FES allowed the products in the demand side to be defined so as to match the SIC definitions traditionally used in supply-side studies. The estimated price elasticities were allocated to the consumer industries in which the firms operate and then included in profitability equations. The household characteristics, also available from the household surveys, were used to construct a unique instrument set, uncorrelated with the firms' supply decisions.

The results indicate that firms, on average, behave noncompetitively. Moreover, the impact of market share on profitability was shown to be higher in more-concentrated industries and in sectors more protected from import competition. This finding gives suport to the "collusion" explanation for the impact of market structure on firms' performance.

The integration of demand-side issues into the standard supply-side framework raises several new questions that were never considered in the literature and that this study has only started to investigate. In this article, for example, the slope of the demand curve was assumed to be constant throughout the sample period, but there are reasons why one might want to relax this assumption and allow the slope to vary over the business cycle, for example. Future work in this area might want to focus on the determinants of the behavior of demand elasticities over the business cycle and their relationship with the cyclicality of markups (see Bils 1989; Chevalier and Scharfstein 1996).

Another potentially interesting idea would be to examine the relationship between income distribution and corporate performance. The price elasticity of the demand for a product, for example, can be decomposed into different elasticities for different levels of the expenditure distribution (see Blundell et al. 1993). Moreover, there is some evidence that the expenditure distribution is correlated with the earnings distribution (see Attanasio and Davis 1996). It would perhaps be interesting to examine whether the recent increases in wage dispersion in the U.K. and U.S., for example, have affected the behavior of firms through their impact on expenditures and demand.

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APPENDIX: DATA

Table A.1. Descriptive Statistics 1: Supply, 1978–1992

Variables	Mean	SD	Minimum	Maximum
Profitability	.076	.069	−.517	.424
Market share	.008	.023	3E−06	.248
Concentration	.405	.224	.060	1
Import penetration	.182	.139	.006	.631

Table A.2. Descriptive Statistics 2: Demand, 1978–1992

Variable	Mean	SD	Minimum	Maximum
Shares				
Cereal	.033	.038	0	1
Bread, biscuits, and crispbreads (BBC)	.155	.077	0	1
Meat	.220	.130	0	1
Fish	.036	.046	0	1
Oils and fats (Oilsf)	.024	.025	0	1
Milk	.194	.097	0	1
Soft drinks (SDrink)	.037	.047	0	1
Sugar	.024	.027	0	1
Sweets and chocolates	.046	.061	0	1
Fruits and vegetables (FVeg)	.156	.095	0	1
Clothing	.678	.401	0	1
Footwear (Fwear)	.159	.276	0	1
Beer	.494	.409	0	1
Wine	.134	.256	0	1
Spirit	.178	.283	0	1
Household consumables	.430	.256	0	1
Toys and sporting goods	.148	.234	0	1
Books and newspapers	.419	.260	0	1
LN (prices)				
Cereal	−.297	.456	−1.444	.312
Bread, biscuits, and crispbreads (BBC)	−.266	.423	−1.293	.320
Meat	−.202	.343	−1.011	.221
Fish	−.326	.423	−1.234	.259

Table A.2 (continued). Descriptive Statistics 2: Demand, 1978–1992

Variable	Mean	SD	Minimum	Maximum
LN (prices)				
Oils and fats	−.091	.235	−.849	.254
Milk	−.297	.493	−1.558	.323
Soft drinks	−.179	.404	−1.270	.446
Sugar	−.187	.388	−1.417	.333
Sweets and chocolates	−.315	.435	−1.584	.214
Fruits and vegetables	−.264	.373	−1.315	.255
Clothing	−.130	.239	−.804	.192
Foowear	−.154	.288	−.883	.221
Beer	−.399	.580	−1.676	.439
Wine	−.161	.323	−.986	.414
Spirits	−.289	.455	−1.277	.449
Household consumables	−.306	.489	−1.549	.214
Toys and sporting goods	−.224	.329	−1.094	.160
Books and newspapers	−.403	.601	−1.788	.441
Stone price indexes				
Food	−.250	.396	−1.255	.266
Alcohol	−.277	.415	−1.173	.366
Clothing	−.119	.214	−.703	.165
Other nondurables	−.337	.512	−1.621	.364

Table A.3. Descriptive Statistics 2: Demand (continued)

Variable	Mean	SD	Minimum	Maximum
Nominal expenditures				
Total nondurables	46.97	38.89	.32	921.53
Food	19.82	13.35	.04	228.28
Alcohol	7.92	12.43	0	871.15
Clothing	12.44	20.14	0	813.04
Other nondurables	6.79	10.37	0	797.14
Other variables				
Total income	156.16	118.45	.19	954.76
First-quarter dummy (S1)	.251	.433	0	1
Second-quarter dummy (S2)	.248	.432	0	1
Third-quarter dummy (S3)	.251	.433	0	1
North	.065	.246	0	1
Yorkshire (Yorks)	.095	.293	0	1
North-West (Nothwes)	.116	.320	0	1
East-Midlands (Eastmid)	.073	.260	0	1
West-Midlands (Westmid)	.099	.298	0	1
East-Anglia (Eanglia)	.036	.186	0	1
Great London (Grlondon)	.114	.318	0	1
Scotland	.097	.296	0	1
South-West (Southwes)	.073	.261	0	1
Wales	.052	.221	0	1
Head white collar (WHC)	.221	.416	0	1
Head professional (PROF)	.100	.299	0	1
Head skilled (Skil)	.275	.447	0	1
Head semi-skilled (SSKIL)	.140	.347	0	1
Children age 0–1 (NK01)	.170	.425	0	5
Children age 2–5 (NK25)	.115	.336	0	3
Children age 6–10 (NK610)	.344	.667	0	7
Children age 11–16 (NK1116)	.325	.655	0	6
Children age 17–18 (NK1718)	.023	.153	0	3
Age of head	40.35	11.27	18	60
Number of pensioners (NNRET)	.025	.194	0	4
Number of females (NNFEMS)	1.049	.500	0	6
Number of adults (ADULTNR)	2.059	.770	1	9
Head single-parent (SGLPAR)	.055	.229	0	1
Car dummy (DCAR)	.705	.456	0	1
Tobacco dummy (DTOB)	.586	.493	0	1
Trend	38.24	21.81	1	76

Table A.4. Matching the SIC With the Product Definitions

SIC code	SIC definition	Product definition	U.S. product definition
411	Organic oils and fats	Oils and fats	Fats and oils
412	Slaughtering of animals and production of meat	Beef + Lamb + Pork+ Poultry + Bacon	Meat
413	Preparation of milk and milk products	Milk + Milk products	Dairy products
414	Processing of fruits and vegetables	Fruits + Vegetables	Fruit/vegetables
415	Fish processing	Fish	Fish and seafood
416	Grain milling	Cereals	Cereal/cereal products
419	Bread, biscuits, and flour confectionary	Bread + Biscuits + Cakes	Bakery products
420	Sugar and sugar by-products	Sugar	Sugar
421	Ice cream, chocolate, and sugar confectionary	Sweets/chocolates	Sweets
428	Soft drinks	Soft drinks	Nonalcoholic beverages
424	Spirit distilling/ compounding	Spirits	Distilled spirits
427	Brewing/malting	Beer	Beer
426	Wine, cider/perry	Wines	Wines
436	Hosiery/knitted Products	Men's + Women's + Children outwear	Apparel commodities Less footwear
451	Footwear	Footwear	Footwear
453	Clothing	Men's + Women's + Children outwear	Apparel commodities Less footwear
258	Soap/toilet preparations	Household Consumables	Toilet goods
475	Printing/publishing	Books and newspapers	Reading materials
494	Toys/sport goods	Toys, photos, and sport goods	Sporting goods, Toys and hoobies

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