Welfare, Market Power, and Price Effects of Product Diversity: Canned Juices

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What effect does the introduction or elimination of a differentiated product have on welfare, market power, and prices? Are there too many of too few differentiated products? To address these questions, we estimate a random-parameter, discrete-choice demand model and then use the estimated demand to calculate the effects of entry and exit on consumer surplus, producer surplus, Lerner measures of price markups, and prices in the canned juice industry.

According to many food and beverage manufacturing executives, brands are maintained through product differentiation (e.g., Nijssen and Van Trijp, 1998). Firms constantly innovate to keep up with changing consumer tastes. Products that are not accepted by consumers are quickly dropped. One might think of this approach of constantly providing new products as a flagpole strategy: "Let's run it up the flagpole and see who salutes it."

New products take two forms. To most of us, the phrase "new product" means a new flavor or other change in the contents of a package, however, in industry parlance, the phrase frequently means putting the contents into a different sized container.

Many firms regularly introduce new flavors and other changes in contents. Snapple introduced two new fruit drinks in 2000: Diet Orange Carrot Fruit Drink and Raspberry Peach Fruit Drink (presumably they are reasoning that if they can sell those, they can sell any flavor).[1] Similarly, Proctor & Gamble extending its line of Punica fruit juice drinks in Germany by launching a canned carbonated drink called Punica Fruitshot in an effort to attract teenagers.[2]

In contrast, Welch's, the marketing arm of the National Grape Cooperative Association Inc., has emphasized changing container sizes. By changing sizes, Welch's products broke out of the one section of the supermarket to which they had been relegated.[3] Now, they are in many

[1] "Fruit Beverages Scope," *Beverage World*, February, 2000, p. 26.
[2] "P&G Launches Carbonated Fruit Juice Drink in Germany," Crain Communications Inc., Euromarketing via E-mail, Vol. 111, No. 19, February 18, 2000.
[3] Chris Reidy, "Welch's Sees Sales Increase as Grape Juice Gains Popularity," *Boston Globe*, January 12, 2000.

supermarket aisles, vending machines, convenience stores, and membership wholesale clubs. Like many other companies, Welch's is introducing at greater rates recently than in the past. About one-third of Welch's sales in 1999 came from products introduced within the last five years; whereas, new products accounted for about only 10 percent of overall sales in the early 1990s.

Economists have written extensively on the theoretical implications of product differentiation on welfare. Spence (1976), Dixit and Stiglitz (1977), Salop (1979), and Deneckere and Rothschild (1986) show that whether there are too few or too many differentiated products depends on the type of equilibrium and on the exact functional forms of demand and costs.

Surprisingly, there have been relatively few empirical studies of the welfare effects of differentiation and innovation. Hausman (1996) and Nevo (2000) look at welfare effects for ready-to-eat cereals; however, they concentrate on the implications for measuring the consumer price index.

More attention has been paid in the empirical literature to the effects of entry on substitution patterns and prices (especially by marketing economists). For example, Kadiyali, Vilcassim, and Chintagunta (1999) examine the price effects of product line extensions. They study two national yogurt manufacturers and conclude that, when a firm introduces a new product or a variant, it gains price-setting power and that the firms' combined sales increase. Hausman (1996) estimates the price effects of a cereal firm's new product on the prices of its other similar products.

We start by discussing the theoretical implications of a linear random utility demand system for oligopoly equilibrium. We then describe how we can estimate such a demand system using a random-parameter model. Next, we describe trends in canned juice sales by U.S. grocery stores. In the following section, we discuss our estimates of demand. We then calculate the market power, price, and welfare effects.

Linear Random Utility Model

We start by discussing the linear random utility model based on the presentations in Perloff and Salop (1985; henceforth PS) and in Anderson, de Palma, and Thisse (1992; henceforth AdPT). In the PS model, we can write a consumer *j*'s conditional indirect utility as[4]

$$\tilde{V}_{ij} = a - p_i + \theta\zeta_{ij},$$

where a is the attribute or quality of a good (initially the same for all goods), p_i is the real price of firm *i*'s product (initially each firm produces a single product), ζ_{ij} is a random variable with mean zero, and θ is the preference intensity: the higher the value of θ, the less important price is in determining which variant a consumer buys. Each of the n firms produces a differentiated product. For simplicity, each of the N consumers buys one unit, so the sum of their demands, Q_i, is N. If ζ_{ij} is distributed IID $F(\cdot)$ with density $f(\cdot)$ and m is the constant marginal cost, the (symmetric) short-run equilibrium price is

$$p = m + \frac{\theta}{n(n-1)\hat{\Gamma}(n)}, \tag{1}$$

where

$$\hat{\Gamma}(n) = \int_{-\infty}^{\infty} f^2(\zeta)[F(\zeta)]^{n-2}\,\mathrm{d}\zeta.$$

Thus, the markup in Equation (1) is proportional to θ and the price, p, is proportional to marginal cost, m.

Increasing the number of firms decreases the short-run equilibrium price iff $(n+1)\hat{\Gamma}(n+1) - (n-1)\hat{\Gamma}(n) > 0$ for an integer number of firms, n. Even though $\hat{\Gamma}(n+1) < \hat{\Gamma}(n)$ by

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[4] The extension of these models to include an outside good is straight forward (cf., Salop, 1979; Perloff and Salop, 1985; Anderson, de Palma, and Thisse, 1992.

inspection, the condition for a price decrease need not hold. Indeed, for some distributions $F(\cdot)$, price may increase with n. One distribution where the price decreases is the logit.

PS show that, when the number of firms become arbitrarily large ($n \rightarrow \infty$), the price approaches the marginal cost if (a) $f(\cdot)$ is bounded from above or if (b) the $\lim_{\zeta \to \infty} f'(\zeta)/f(\zeta) = -\infty$ when the support from above is unbounded. For example given the upper bound condition in (a), as the number of firms grows very large, consumers find more varieties that they value near the upper bound of the support of the density function, so that competition drives price to marginal cost. A similar intuition applies for condition (b). For probit, condition (b) holds so that the limit is perfect competition. However, if neither condition (a) nor (b) holds, the limiting case is monopolistic competition with price strictly above marginal cost. With the logit distribution, the equilibrium price falls monotonically with n to a limit of $m + \mu$.[5] The limiting case is relevant if either the size of the market becomes arbitrarily large or if the fixed cost becomes arbitrarily small.[6]

Now we consider a generalization of the linear random utility models in PS and AdPT. Each firm sells one or more products, where i is the product index and n is the total number of products across all firms. In each period, the indirect utility for consumer j is

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[5] The limit occurs where $\mu = \sigma\sqrt{6}/\pi$ (AdPT, p. 188). Even more striking as PS show, the limit for the standardized exponential is $m + \mu$ and the price is independent of n for $n \geqq 2$.

[6] With free entry, then the long-run equilibrium number of firms is uniquely determined as the implicit solution to (AdPT, p. 189): $n^2(n-1)\hat{\Gamma}(n) = N\theta/K$ where K is the fixed production cost per firm.

$$\tilde{V}_{ij} = a_i - p_i + \varepsilon_{ij} + \zeta_{ij},$$

where ε_{ij} is distributed multivariate normal and ζ_{ij} is distributed IID extreme value. By using two error terms with different distributions, we avoid forcing the equilibrium to have the particular properties of either the logit or the probit. We could weight these two error terms to allow the model to range between the two extremes.

By integrating to concentrate out ζ_{ij}, we derive multinomial logit share equation for item *i* purchased by individual *j*:

$$\tilde{S}_{ij} = \frac{e^{(a_i - p_i + \varepsilon_{ij})/\mu}}{\sum_{k=1}^{n} e^{(a_k - p_k + \varepsilon_{kj})/\mu}}, \tag{2}$$

where μ is the scale parameter on the type 1 extreme value. By integrating over individuals *j*, we can concentrate out the ε_{ij} terms and obtain the item's share:

$$S_i = \int \tilde{S}_{ij} f(\varepsilon) \mathrm{d}\varepsilon. \tag{3}$$

Consequently, if each consumer buys one unit (or any constant number) so that the total number of units purchased is *N*, then the demand equations are

$$Q_i = NS_i. \tag{4}$$

Although one interpretation of μ in these equations is the scale parameter, AdPT (p. 78) provide another way of viewing it. They show that a representative consumer's utility function (where we suppress the individual's index) consistent with these multinomial logit share equations is given by

$$U = \begin{cases} \sum_{i=1}^{n} a_i Q_i - \mu \sum_{i=1}^{n} Q_i \ln \frac{Q_i}{N} + Q_0 & \textit{if } \sum_{i=1}^{n} Q_i = N, \\ -\infty & \text{otherwise} \end{cases} \tag{5}$$

where Q_0 is an outside good. The second term on the right-hand side of Equation (5) is μN times a version of the entropy measure. It captures the variety-seeking behavior of the representative consumer. All else the same, the larger is μ (which plays a role similar to θ in the PS model), the greater is the preference for diversity. When $\mu \to 0$, diversity is not valued per se and the consumer buys solely the variant with the largest net surplus, $a_i - p_i$; and when $\mu \to \infty$, consumption is divided equally among all available variants.

We can now use these demand equations to derive a firm's multiproduct optimal pricing strategy. We start by examining how an item's share varies with item price, which we obtain by differentiating Equation (3):

$$\frac{\partial S_i}{\partial p_i} = \frac{1}{\mu} \int \tilde{S}_{ij} \left(\tilde{S}_{ij} - 1 \right) f\left(\varepsilon\right) \mathrm{d}\varepsilon. \tag{6}$$

In setting its prices, the firm must take into account how changing the price of one item in its product line can cannibalize the demand of another item. In each period, suppose that a given firm sells h products, so that it maximizes its profit of

$$\pi = \sum_{k=1}^{m} \left(p_k - m_k \right) Q_k - hF - \tilde{F}, \tag{7}$$

where the time parameter is suppressed, k indexes only those items sold by that particular firm, marginal cost per item is constant at m_k, the fixed cost associated with item k for that firm is F, and the overall fixed cost for the firm is $\tilde{F}$. The firms' equilibrium is Nash-Bertrand. Using Equation (6), we can write the first-order condition for profit maximization of Equation (7) as[7]

$$\frac{\partial \pi}{\partial p_k} = \sum_l \left(p_l - m_l\right) \frac{N}{\mu} \int S_{kj}\left(S_{kj} - 1\right) f\left(\varepsilon\right) \mathrm{d}\varepsilon + NS_k = 0 .$$

By rearranging terms, we find that

$$\sum_l \left(p_l - m_l\right) = \frac{\mu S_k}{S_k - \int \tilde{S}_{kj}^2 f\left(\varepsilon\right) \mathrm{d}\varepsilon}, \tag{8}$$

for each firm.

Whether there is too little or too much diversity depends, in part, on whether competition is localized - as in a spatial or Hotelling model (Salop, 1979)—or all firms compete with each other—as in a representative consumer or Chamberlin model (Spence 1975, Dixit and Stiglitz 1976, and Perloff and Salop 1985). Deneckere and Rothschild (1992) construct a model of demand that nests the Salop (1979) and Perloff and Salop (1985) models. Deneckere and Rothschild show that adding an extra brand benefits fewer consumers in a spatial model (where competition is localized) than in a representative consumer model. Consequently, there are too many brands in a spatial model but may be too many or too few in a representative consumer model.

[7] We do not model tie-in sales due to a lack of information. An example is that Tropicana juices benefit from "cross-marketing programs" with other PepsiCo brands, where discounts are given on one brand when another is purchased. Gary Haber, "Florida-Based Juice Maker Tropicana Posts 70 Percent Gain in Earnings," *Tampa Tribune*, April 21, 2000.

Estimating the Random-Parameter Model

We want to estimate this model so as to calculate the effect of entry or exit on welfare and elasticities of demand. To do so, we use a random-parameter discrete-choice model of individual consumer behavior that corresponds to our theoretical model (cf, Berry, Levinsohn, and Pakes, 1995; Train, 1998).

Consumers' choices vary, but we do not have information about individuals' choices or their personal characteristics. We only have data on their aggregate consumption. Thus, we model demand as depending on observed and unobserved (by the econometrician) product characteristics and price. We capture these unobserved effects using random parameters.

Consumer *j* chooses an item *i* produced each period *t*. Consumer *j*'s conditional indirect utility is

$$\tilde{V}_{\mathrm{ijt}} = X_{\mathrm{it}}\beta_{\mathrm{j}} + \zeta_{ijt},$$

where X_{it} is a vector of observed product characteristics, β_{j} is a vector of coefficients that are unobserved for each consumer *j* and that vary randomly over consumers due to differences in tastes, and ζ_{ijt} is an unobserved random term.

We can arbitrarily choose which distribution to use with our random-parameter model. Many researchers use random-parameter logit (RPL), a generalization of logit, but there are many other possibilities such as random-parameter probit. We assume that ζ_{ijt} is distributed IID extreme value independently of β_{j} and X_{it}.

RPL allows coefficients β_{j} to vary across the population rather than being common for all. We decompose the coefficient vector for each consumer, β_{j}, into the sum of the population mean,

β, and an individual deviation, η_j, that represents the consumer's taste relative to the average tastes of all consumers. We assume that η_j is distributed IID normal. We can rewrite utility as

$$\tilde{V}_{ijt} = X_{it}\left(\beta + \eta_j\right) + \zeta_{ijt} \equiv X_{it}\beta + \varepsilon_{ijt} + \zeta_{ijt}.$$

As we show below, we can estimate β, but we do not observe η_j for each consumer. Thus, the unobserved portion of utility is $X_{it}\eta_j + \zeta_{ijt} \equiv \varepsilon_{ijt} + \zeta_{ijt}$. This term is correlated over products and time because of the common term η_j. That is, we assume that a given consumer has the same tastes over products and time (however, we allow some product characteristics to vary over time by adding interactions between those characteristics and a time trend).

RPL generalizes logit by allowing the coefficients of characteristics to vary randomly over characteristics rather than be fixed. RPL avoids three unattractive restrictions of the usual logit or nested logit models that have traditionally been employed in demand studies (Train, 1998). First, in logit or nested logit models, the coefficients of variables that enter the model are assumed to be the same for all products, which implies that different products with the same observed characteristics have the same value for each factor. Consequently, the logit predicts that a change in the attributes of one alternative changes the probabilities of the other alternatives proportionately (and the nested logit makes the same assumption within a nest). Second, the logit model has the "independence from irrelevant alternatives" (IIA) property, and nested logit has IIA within each nest. Third, where repeated choices are made over time, logit and nested logit assume that unobserved factors are independent over time (in the absence of time trend terms).

In contrast, the RPL allows the unobserved portion of utility to be correlated across products and time. Consequently, RPL coefficients are not the same across all products, and RPL lacks the IIA property of the traditional logit or nested logit models, and choices may vary over time. For example, we allow consumers' tastes for certain types of products (e.g., sparkling juice drink) to change over time. Indeed, the RPL model can exhibit very general patterns of correlation over products and time. McFadden and Train (2000) show that any pattern of substitution can be represented arbitrarily closely by a RPL.[8]

Suppressing the time, t, index, noting that $a_i \equiv X_i\beta$ and $\varepsilon_{ij} \equiv X_i\eta_j$, and integrating out the ζ_{ij} term that is distributed IID extreme value, we can rewrite share Equation (2) as

$$\tilde{S}_{ij} = \frac{e^{(X_i\beta - p_i + \varepsilon_{ij})/\mu}}{\sum_{l=1}^{n} e^{(X_l\beta - p_l + \varepsilon_{lj})/\mu}}. \quad (9)$$

We now integrate out the population distribution of the taste parameter ε_{ij}, which is distributed IID normal to obtain Equation (3):

$$S_i = \int \tilde{S}_{ij} f(\varepsilon) \mathrm{d}\varepsilon.$$

We cannot evaluate the product shares directly because the high-dimensional integral is difficult to calculate analytically. Instead, we approximate the product share using simulations. In particular, S_i is approximated by a sum over randomly chosen values of ε_{ij}. A value of ε_{ij} is drawn from its distribution and used to calculate the share in Equation (3). This process is repeated for 50 draws, and the average of the share $\tilde{S}_{ij}$ is taken as the approximate choice probability. By construction, we have an unbiased estimator, whose variance decreases as the number of draws increases. The simulated estimator is smooth (e.g., twice differentiable), which

[8] Actual substitution patterns may be complex. For example, Allenby and Rossi (1991) find that consumers are more likely to switch up to high-quality brands than down in response to price promotions.

helps in the numerical search for the maximum of the simulated log-likelihood function. It is strictly positive for any realization of the finite draws, so that the log of the simulated probability is always defined. See Lee (1992) and Hajivassiliou and Ruud (1994) for the asymptotic distribution of the maximum simulated likelihood estimator based on smooth probability simulators with the number of repetitions increasing with sample size. Under regularity conditions, the estimator is consistent and asymptotically normal (McFadden, 1989). When the number of repetition rises faster than the square root of the number of observations, the estimator is asymptotically equivalent to the maximum likelihood estimator.

Similarly, we can calculate the associated expenditure function (cf., AdPT, p. 79):

$$Z = \bar{U} - N\mu \ln\left[\int \sum_{i=1}^{n} e^{(a_i - p_i + \varepsilon_{ij})/\mu} f(\varepsilon)\mathrm{d}\varepsilon\right]. \tag{10}$$

for any utility level $\bar{U}$. This expression provides the dollar value of the exact consumer benefit from increased product variety.

Finally, we calculate the own and cross-price elasticities of demand, which we use later to predict price changes. The own price elasticity for item *i* is

$$E_{ii} = \frac{p_i}{\mu S_i} \int \tilde{S}_{ij}\left(\tilde{S}_{ij} - 1\right) f\left(\varepsilon\right) \mathrm{d}\varepsilon \tag{11}$$

which must be negative. If we used a traditional logit, this expression simplifies to $E_{\mathrm{ii}} = p_{\mathrm{i}}\left(S_{\mathrm{i}} - 1\right)/\mu$. Thus, own price elasticity is roughly proportional to own price. The cross-price elasticity (effect of a change in the price of good *k* on the quantity of good *i*) is

$$E_{ik} = \frac{p_k}{\mu S_i} \int \tilde{S}_{ij} \tilde{S}_{kj} f\left(\varepsilon\right) \mathrm{d}\varepsilon \tag{12}$$

which must be positive (all goods are substitutes). With a standard logit, the cross-price elasticity simplifies to $E_{ik} = p_k S_k / \mu$.

In Appendix 1, we prove that an increase in one good's price, holding all other goods' prices fixed, causes the shares of other goods to rise for *any* discrete-choice model. For the logit, eliminating a good causes other goods' shares to rise, increasing their own price elasticities. Consequently, the price of all other goods will rise in a logit model where each firm produces a single good. However, in our more general model, the elasticity, and hence price, may rise or fall (as we illustrate with our estimates). Thus, by generalizing the logit model, we obtain greater flexibility in elasticities and pricing.

Canned Juice Summary Statistics

We now describe the U.S. grocery store canned juice industry. Throughout this paper, we use grocery store scanner data (Information Resources Incorporated's InfoScan™), which is described in Appendix 2. The data set covers 29 time periods of four weeks each, which we call *months* (though we should call them "februaries"). Thus, there are 13 months per year and the sample covers about 23 years. The first month in the sample ended on December 8, 1996, and the last one on January 31, 1999.

Trends

The following summary statistics are based on the full sample. The estimation results are based on a restricted sample (see Appendix 2).

Branded canned juices had an 80.2% quantity share compared to 19.7% for private labels alone and 19.8% for private labels and generics. Henceforth, we treat both private label and generics as one group, which we (inaccurately) call *private-label* goods. Over our time period, the canned juice private label share had an 11.4% annual growth rate.

The average real price of all juices was 53¢ per pint, compared to 57¢ for branded, and 41¢ for private labels. Averaged over the period, private labels' price was 72.2% of the branded goods' price. Consequently, there is either a substantial cost or quality difference between branded and private label products or the branded goods can exercise substantially more market power than can private labels. There was no price trend overall; the price of branded goods rose at a 1.1% annual rate, while the price of private labels fell at a 1.2% rate.

The quantity shares of the largest firms differ less than in most other food sectors that we have examined.[9] The largest firm has a 19.2% share; the second, 17.6%; the third, 11.5%; the fourth, 4.6%; firms 5 through 8 collectively, 10.7%; and smaller branded firms collectively, 16.6%. The largest firm lost 4.1% of its share per year (over the last couple of years), while the next largest lost 5.1% per year. Thus, the industry shares have been become more uniform over time. The Gini coefficient over shares of items was 0.90 and the Gini over firms was 0.94. The items Gini fell at a 0.30% per year, while the firm Gini grew at a 0.08% rate.

We regressed the log of the quantity share of each of the eight largest firms on the log of the private label share and seasonal dummies. The estimated elasticity of the largest firm's share with respect to the private label share was -0.36 for the largest firm and 0.68 for the second largest. The elasticity for the share of the ninth and smaller branded firms was 0.36. On the basis of t-tests, we

[9] Out of 32 food industries chosen randomly, the largest firm had a smaller share than in canned juice in only 8. Of the rest, the share of the largest firm ranged from 25.6% to 78.2%. Moreover, in virtually every other sector, the second largest firm's share was substantially smaller than that of the largest.

reject the hypothesis that any of these three elasticities is 0 at the 0.05 level. We could not reject the null hypothesis for the second through eight largest firms. The elasticity of the item Gini with respect to the private label share is -0.02 (and statistically significantly different from 0), while the firm Gini elasticity is almost exactly 0.

In each month, the average number of branded canned juice items was 767.2, the number of brands was 230.2, and the number of brand-name firms was 174.4. The corresponding annual growth rates were -1.11% (not statistically different from 0), 2.17%, and 1.98%. Quantity in this sector fell at a -6.46% annual rate.

The average number of items per firm was 4.39, brands per firm was 1.32, and items per total quantity was 0.79. The number of items per firm fell at 3.09% per year, while the number of items per quantity grew at a 5.35% annual rate. The elasticity with respect to the private label share was -0.09 for items (not significantly different from zero), 0.02 for firms (not statistically different from zero, and -0.23 for items per firm.

The average number of item births per firm per month was 0.15, as was the average number of deaths, so the total number of items relatively constant over time. The correlation coefficient for births versus deaths was 0.15 for items, -0.28 for brands, and -0.24 for firms.

On average, the quantity share of births to all items was 0.19, whereas the ratio for deaths was 0.15. The price of births to that of continuing products averaged 1.04, the same ratio as for eliminated products to continuing products.

On average 9.7% of items were on sale (temporary price reductions), but this share fell 8.5% annually. The share of items on nonprice promotions (local feature ads and in-store displays) was 19.5%, which fell at a 9.7% annual rate. The elasticity of the share of promotions with respect to private label share was 0.58 for sales promotions (not statistically significantly different from 0) and -0.84 for nonprice promotions.

We estimated that the elasticity of the price of individual brand-name firms with respect to private label share (controlling for seasonality). Starting with the largest firm, the (statistically significant different from zero) elasticities were 0.09, 0.17, 0.37, and 0.37. The elasticities for fifth through eighth largest firms and the smaller firms collectively were not statistically significantly different from zero. Thus, as private labels enter, large name-brand firms raise their prices, while smaller ones apparently do not change their prices. Overall, the elasticity of the price of all branded firms with respect to private label share was 0.13. The elasticity of the price of private label goods with respect to private label share was -0.14. Consequently the elasticity of the overall price with respect to private label share was approximately zero (0.02 but not statistically significantly different from 0).

Popular Canned Products

The most popular canned product flavors in order are vegetable, fruit punch, tomato, pineapple, apple, grape, and citrus. The most popular types of canned drinks in our sample in order are juice, juice drink, nectar, and juice cocktail. The most popular counts of cans sold (number of cans packaged together) are 1, 6, 12, 24, and 4 in that order. Table 1 shows the 10 best selling items.

Estimation Results

We used the IRI data to estimate a random-parameter demand model. Each observation is for an item in a given month. An item is a variant of a brand, where items may differ in size, the number of cans in a package, flavor, or in other ways.

The explanatory variables include price, the share of sales for which the item was being promoted (a special display in the store, a local feature advertisement, or both a display and a feature advertisement), size (total quantity in ounces in a package), count (number of cans in a package), size/count (size of each can within a package), a time trend (1, 2,...) interacted with the types of products (juice, nectar, sparkling juice,...), and a dummy for each brand (such as Dole's Pineapple Juice). Our specification does not include firm dummies because they are perfectly collinear with the brand dummies. Similarly, it does not include dummies for flavor because they would be nearly collinear with the brand dummies. The estimated model includes error components for flavors (28), types (8), firms (70), brands (104), items (421), size, count, and size/count.

We use 50 draws for each error component. The maximum likelihood estimates are reported in Table 2, where we report the coefficients as β/μ. On the basis of asymptotic t-tests, we reject at the 0.05 level the null hypothesis that the coefficient is zero for price, count, time x juice (which was growing), and time x sparkling juice (which was dying at a rapid rate); the scale terms on the error components for flavor, type, and brand; and all but 2 of the brand-specific dummies (which are not reported in the table to save space). One might view a positive brand dummy as a measure of high quality or market power.

The diversity coefficient, μ, equals the negative of the reciprocal of the price coefficient: $\mu = 0.275 = -1/[-3.6376]$. Its asymptotic standard error is 0.0058, so we reject the hypothesis that it equals 0. Nonetheless, μ is relatively close to 0 (and far from ∞). When $\mu = 0$, the consumer buys only the variant with the largest net surplus and hence does not place a large value on diversity. Thus, we find that consumers place a very slight (statistically significant) value on diversity.

Endogeneity

Unobserved quality variation may introduce spurious correlation between average price and average sales across brands. A low-quality brand would tend to have fewer sales than other brands for some fixed price. However, the low-quality item is likely to be paired with a relatively low price, because price is chosen optimally by the firm. To account for this source of endogeneity, we use a fixed-effects model with a dummy for each brand to capture unobserved quality variation at the brand level.[10] The regression coefficients are identified by time-series variation in the explanatory variables and not by cross-sectional variation. As the asymptotic t-statistics on these brand dummies are enormous (often in the hundreds), a Hausman test strongly rejects the alternative hypothesis of random effects.

One might still be concerned about endogeneity and wish to use instruments. Following Hausman (1996), some researchers who have a cross section of city data over time have used argued that city-specific valuations of products are independent across cities but are correlated within a city over time. They then argue that prices of a brand in another city are a valid instrument because prices are correlated across cities due to a common marginal cost. We find the cross-city independence assumption difficult to believe especially for firms that engage in national advertising. An alternative approach is to use cost data that vary across products.[11]

[10] Because we have 29 time periods, we are not concerned about the identification issue that Chamberlain (1982) raised.

[11] We have reestimated the model with farm-gate prices (for oranges, tomatoes, and so forth) as instruments and found very similar results.

Market Power

We can use the estimated demand system to infer the degree of market power and marginal costs if we are willing to make certain strong assumptions. We assume that the manufacturing marginal cost is constant and that grocery stores add a constant markup (which might be the case if they are competitive), so that the total marginal cost of selling a can is *m*. Presumably grocery stores have a fixed-proportions production function where they sell cans in proportion to those they purchase from the manufacturer. If so, the final equilibrium is the same as if a down-stream firm with market power were to vertically integrate into retailing (see, e.g., Carlton and Perloff, 2000).

Given our assumptions, the Lerner measure of market power depends on the elasticities of demand. If a firm makes a single product and maximize its profit, the relevant Lerner index is $L = (p - m)/p = -1/e$, where *e* is its own price elasticity. On the other hand, if the firm produces many products and engages in a Bertrand-Nash game with other firms, then its first-order conditions for profit maximization are given by Equation (8).

Alternatively, the vector of Lerner markups can be written in terms of cross-price elasticities (see, e.g., Hausman 1996):

$$\hat{L} = -\left(E'\right)^{-1} S,$$

where *S* is the vector of the shares of the items and is a vector whose k^{th} element is L_k, the Lerner price-cost markup for item *k*, times S_k, item *k*'s share (of the firms total sales). Thus, the Lerner index for item *k*, L_k, is the k^{th} row of the (inverted transposed) matrix times the column vector *S* divided by S_k. Essentially what this equation tells us is that the relevant elasticity of demand for the item is a weighted average of its own price elasticity and the cross-price elasticities of the other items the firm makes. We call this weighted elasticity the *multiproduct elasticity*.

The matrix E has negative own-price elasticities on the diagonal and positive cross-price elasticities—all items are substitutes—off the diagonal [see Equations (11) and (12)]. As the firm lowers the price of one item, it sells more of that item (because its own price elasticity is negative) but it cannibalizes sales from its other items (due to the positive cross elasticities). Consequently, the multiproduct elasticity for an item is less elastic than is the own-price elasticity.

Price Effects

Holding our calculated marginal cost constant, we can use our optimality equations to predict the effect of an entry or exit (which effectively drives the price of the good to ∞) on the prices of other products. We allow all prices to adjust until a new equilibrium is achieved. We calculate the average price change from period 0 to period 1 as the change in revenue due to the price change divided by the revenue in period 0:

$$\frac{\sum_i \left[p_i(1)-p_i(0)\right]q_i(0)}{\sum_i p_i(0)q_i(0)}.$$

Table 3 shows three thought experiments in which we remove existing products. If we eliminate Dole's 46 ounce can of pineapple juice (the second best selling item across all brands), Dole lowers its price on its other product, a six-pack of six ounce cans of pineapple juice, by 4.1%. Other firms raise their prices on their pineapple products by an average of 0.3% and the price on other (non-pineapple) products by an average of 0.8%.

Were we to eliminate Dole and both its products, the price on other pineapple products would rise by 0.8%, while the price on other products would increase by 0.9%. Finally, if we were to eliminate all pineapple juices, the prices of other products would rise by 1.0%.

Welfare

Next we use our estimates to examine the various welfare effects of entry and exit, holding price fixed. Given that, by assumption, income is fixed in our model, the compensating variation (CV) and equivalent variation (EV) measures of the change in consumer surplus are the same. They are calculated as changes in the expenditure function in Equation (10). Producer surplus is the price minus the average variable cost (which equals the marginal cost) times quantity. This producer surplus measure is an upper bound on a firm's profit because it does not include firm and brand fixed costs.

Pineapple Experiment

We can determine the welfare value of an item, brand, firm, or flavor by asking what happens if it is eliminated (effectively driving the price of this product to a choke price, possibly ∞). We illustrate this approach in Table 4 using pineapple juice products.

Suppose that Dole were forced to stop selling its 46 ounce can of pineapple juice, which has revenues of $1.5 million dollars per month (5% of the total revenue in our restricted sample). If we hold all other prices fixed, the compensating variation to offset this loss of a product for consumers is about $345,000 per month. If we allow prices to change, then the compensating variation is $495,000 per month (44% more than if we hold prices fixed).

If Dole eliminated this product and total quantity remains unchanged, 5.8% of this quantity would go to Dole's other product, a six-pack of six ounce cans of pineapple juice. Other pineapple juices would get 3.4% of the quantity, and all other products collectively would gain the remaining 90.7%. Apparently consumers do not view small cans of Dole pineapple juice as extremely close substitutes for its large cans.

The producer surplus loss is slightly larger without the price effects (-$355,000) than with them (-$796,000). The welfare falls more after the price adjusts (-$796,000) than without the adjustment (-$700,000).

Now suppose that Dole (and hence both of its products) was forced to exit the industry. The consumer surplus loss is $1.18 million per month taking account of price adjustments. The other pineapple juices would gain 3.7% of the quantity and other products would gain 96%. The welfare loss, -$766,000 per month, is actually less than from eliminating only the large Dole can because of the producer surplus gains by other firms.

Finally, suppose all pineapple juices were eliminated. The consumer surplus loss is $1.68 million per month if prices are allowed to vary. Thus, most of the consumer surplus from pineapple juice is attributable to Dole. The welfare loss is -$957,000, not much larger than the loss from eliminating only Dole's 46 ounce can.

Actual Entries and Exits

We can also use our model to examine the effects from actual entries and exits. The compensated variation net effects from all the entries and exits in each month exhibit a monotonic downward trend over time. Over the entire period, compensated variation fell by about one percent. We now turn to a case of "near" entry and one of "near" exit.

Jugos was a major "near" entrant during our period, going from trivial sales of Del Valle nectar and nectar drinks to total revenue in the final month of $274,000. As Table 5 shows, the consumer surplus gain taking price adjustments into account from this firm's entry was $130,300 per month, the producer surplus gain was $51,600 per month, and the welfare gain was $181,800 per month (evaluated in the last period). Thus, consumers gained two and a half times as much as did the firms (in net) from this entry.

Over our period, the size of Conagra's vegetable juice division, which manufactured Hunt's tomato juice, dropped substantially. The firm went from combined revenues of about $410,000 a month in the first month to essentially 0 by the end of the period. Accounting for price adjustments, the consumer surplus loss due to this "exit" was $52,400 per month (evaluated in the first period). The producer surplus loss was $227,900 (the other producers received little benefit) so that the welfare loss was $280,200 per month. Thus, consumers suffered relatively little loss from removing these products—which presumably explains why their sales disappeared.

Valuing the Eight Largest Firms

What would happen if one of the eight largest firms shut down? We answer this hypothetical question in Table 6, where we treat the two divisions of Nestle—canned fruit juice and canned drink—as separate firms (as they are recorded in the IRI data). The first three columns show the changes in producer surplus, consumer surplus, and welfare if we eliminate one of these firms. The last column shows the magnitude of the change in welfare relative to the revenue of that firm. For six of these large firms, other firms would benefit if one of these large firms were shut down. Indeed, total producer surplus rises. However, consumers lose substantially and total welfare falls if any of these firms is eliminated. Indeed, as the (million) dollar amounts in the table are for a single month, the loss to society of shutting down any one of these firms is large. If we plot the consumer surplus losses from eliminating each firm plotted against that firm's revenue, the dots in the figure lie almost exactly on a straight line with a slope of one, showing that consumer surplus rise in proportion to revenue.

Summary and Conclusions

We estimated a system of demands for canned juices using a random-parameter, discrete-choice model that uses a type one extreme value error and other errors that are distributed normal. Consequently, our demand system allows for much more complex substitution patterns than do standard logit, nested logit, or probit models, and our oligopoly model is not as restrictive as it would be with a standard logit or probit model. We include a larger number of firms and items in our demand estimates than most previous studies. Indeed, most if not all other similar studies have aggregated item level data to the brand level before estimating and include only a small subset of the major brands.

Based on our estimates, we find that consumers put a relatively low value on diversity. Canned juice companies exercise substantial market power, with Lerner indexes substantially above zero. Eliminating an item, brand, or flavor leads to only moderately price changes in other products.

The entry or exit of an item, brand, or firm tends to have a larger welfare effect if price is allowed to adjust. The gain or loss of one of the major firms has large welfare effects—generally in excess of, but of the same order of magnitude as—that firm's revenue. In the next version of this paper, we hope to extend our analysis by explicitly studying whether there is too little or too much variety and by examining the effects of mergers.

Appendix 1: Discrete-Choice Model Results

For any discrete-choice model, an increase in the price of one good implies that the share of each of the other goods must rise. Let the conditional indirect utility for good *i* be

$$\tilde{V} = X_i\beta - p_i + \varepsilon_i.$$

Then the probability that a consumer chooses good *i* over any of the other *n* goods is

$$\Pr\left\{\tilde{V}_i > \tilde{V}_1, \tilde{V}_i > \tilde{V}_2, \ldots, \tilde{V}_i > \tilde{V}_n\right\},$$

or

$$\Pr\left\{(X_i - X_1)\beta + p_1 - p_i + \varepsilon_i > \varepsilon_1, \ldots, (X_i - X_n)\beta + p_n - p_i + \varepsilon_i > \varepsilon_n\right\},$$

or

$$\Pi_j\, F\left(\left[X_i - X_j\right]\beta + p_j - p_i + \varepsilon_i\right),$$

where *F* is a cumulative density function. By inspection, $\partial F/\partial p_j > 0$, so the probability that a consumer purchases this good (the good's share) rises as the price of another good increases.

Appendix 2: Data Sources

We use Information Resources Incorporated's (IRI) InfoScan™ data. IRI obtains data on all items scanned at cash registers from 11,300 local grocery stores from across the United States. The data are then scaled up to reflect all the sales in stores with revenues of $2 million and greater.

The InfoScan database contains information on dollar sales and physical volumes of food products at the brand and UPC (universal product code) or item level. The database also contains the share of dollar sales and physical volume sold on promotion (price reduction, special display, retail ads, and any other type of promotion excluding coupons).

IRI obtains between 90% and 92% of its scanner information from major chains that provide IRI with a *census*: complete information from all of the chain's stores. As these data are inclusive, no scale adjustment is required to convert this information to national levels. Random stratified sampling is used for the remaining (primarily nonchain) stores. A rotating panel design (similar to government surveys) is used where a fraction of the stores are dropped from the panel each month and replaced by others. Information about the entry and exit of stores is obtained from the census and random stratified sampling information and from field personnel. The random stratified sampling data are then projected to national levels.

The individual *item* data we use were drawn from the U.S. Department of Agriculture's Economic Research Service=s version of the InfoScan database, which contains 519 different product *types*, which are in turn subsets of 166 product *categories* from 5 major supermarket *departments* (edible groceries, frozen food, bakery, dairy, and deli). We use data from one category: canned juices.

Local promotion information is collected by IRI field auditors on a weekly basis and used to develop physical and sales volume measures of food products sold under promotion and merchandising. The auditors track and classify the use of displays, retail ads, and any other retailer merchandising efforts. Promotion information is assembled each week and merged with weekly scanner data. The information allows IRI to differentiate regular everyday sales from sales made under promotion or special merchandising. The Economic Research Service database provides 10 promotion measures (5 for dollar sales and 5 for physical volume), which reflect the share of sales and physical volume sold under price reduction, display, feature, feature and display, and any individual or combined use of these promotions. Price reduction refers to items with temporary sale prices; display, to aisle or end displays; feature, to items that are primarily advertised in local papers or paper inserts; feature and display, to items that are both advertised and on display.

All prices are in real dollars. We deflate by the Consumer Price Index, where the index is normalized to equal one in the first month.

We restrict our sample to the 28 best selling flavors. In addition to apple, grape, orange, and tomato, it includes apricot, citrus, fruit punch, guava, tropical, vegetable, white grape and many others. The data set also includes 8 types of drinks including drink, juice, juice cocktail, juice drink, and nectar. A package many have seven different "counts" of containers: 1, 2, 3, 4, 6, 12, or 24. The size per container is recorded in ounces.

We excluded firms that never had any item that sold more than 3,000 pints in any month. The reason for this restriction is that sales of smaller firms are extremely variable, which may reflect substantial measurement errors. In addition, we eliminated items for which, during certain months, the price exceeded the normal price by 250%, again on the grounds that these variant prices are almost certainly measurement errors.

Using the entire sample, the average number of firms in each month is 174, the number of brands is 230, and the number of items is 767. After restricting the number of flavors, we have 150 firms, 191 brands, and 613 items. After eliminating very small firms and those with implausible price fluctuations, we have 70 firms, 104 brands, and 421 items. The restricted sample has 9,132 observations, which is fewer than 421 items x 29 months because not all items are available in each month.

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Table 1: 10 Best Selling Items

	Size (ounces)	*QuantityPercentage of Best Seller*
V8 Canned Vegetable Juice/Cocktail (Campbell Soup Co.)	46	100
Dole Pineapple Canned Fruit Juice (Dole Foods Co.)	46	64
Juicy Juice Fruit Punch (Nestle S.A.)	46	61
Seneca Apple Juice (Seneca Foods Corp.)	46	52
Juicy Juice Grape Juice (Nestle S.A.)	46	49
Campbell's Tomato Juice (Campbell Soup Co.)	46	49
Juicy Juice Cherry Juice (Nestle S.A.)	46	48
Juicy Juice Berry Blend Juice (Nestle S.A.)	46	48
V8 Canned Vegetable Juice/Cocktail (Campbell Soup Co.) 6 count	69	46
Hawaiian Punch Canned Juice Drink (Procter & Gamble) 12 count	144	44

Table 2: Maximum Likelihood Estimates

	Coefficient (β/μ)	*Asymptotic Standard Error*
Continuous Variables		
Price ($)	-3.6376	0.0762
Feature and Display (% of sales)	0.0360	0.0222
Display Only (%)	0.0117	0.0109
Feature Only (%)	-0.0034	0.0189
Size (ounces)	-0.0108	0.0062
Count (number of cans)	0.0984	0.0348
Size/Count	0.0135	0.0236
Drink H Time	0.0550	0.1082
Juice H Time	0.1722	0.0746
Juice Cocktail H Time	-0.0682	0.2028
Juice Drink H Time	0.0455	0.0692
Nectar Drink H Time	0.0052	0.1653
Nectar H Time	0.0843	0.0688
Sparkling Juice Drink H Time	-0.2940	0.0143
Error Scale Terms		
Flavor	0.5147	0.1971
Firm	0.4484	0.2326
Type	2.1722	0.2170
Brand	0.3680	0.0665
Item	0.3366	0.3786
Size	0.0008	0.0061
Count	0.0159	0.0674
Size/Count	0.0566	0.0677

Notes:
(1) The sample size is 9,132. The sample was restricted to those firms that sold more than 3,000 pints in each month.
(2) The brand-specific dummies are not reported to save space (all but two have asymptotic t-statistics that are greater than 2, and most are very large).
(3) The simulation used 50 draws.

Table 3: Price Effects from Eliminating Pineapple Juice Products

	Price Effect (%) on		
Eliminate Pineapple Products	*Dole's 6-Pack of 6 oz Cans*	*Other Pineapple Products*	*Non-Pineapple Products*
Dole's 46 oz can	-4.1	0.3	0.8
All Dole products	-	0.8	0.9
All pineapple products	-	-	1.0

Table 4: Welfare Effects from Eliminating Pineapple Juice Products
($ thousand per month)

	Vary	
Eliminate Pineapple Products	*Quantity Only*	*Quantity and Price*
Eliminate Dole 46 oz		
Consumer Surplus	-345	-495
Producer Surplus	-355	-301
Welfare	-700	-796
Eliminate all Dole		
Consumer Surplus	-916	-1,183
Producer Surplus	210	417
Welfare	-706	-766
Eliminate all pineapple		
Consumer Surplus	-1,391	-1,677
Producer Surplus	497	720
Welfare	-894	-957

Table 5: Welfare Effects from Entries and Exits
($ thousand per month)

	Varying	
	Quantity Only	*Quantity and Price*
"Entry" by Jugos		
Consumer Surplus	84.3	130.3
Producer Surplus	85.6	51.6
Welfare	169.9	181.8
"Exit" by Conagra		
Consumer Surplus	-20.8	-52.4
Producer Surplus	-248.9	-227.9
Welfare	-269.7	-280.2

Table 6: Welfare Effects from Removing One of the Eight Largest Firms

Allowing Prices to Adjust
($ real million per month)

	Change in			
	Producer Surplus	*Consumer Surplus*	*Welfare*	$\frac{\lvert \Delta Welfare \rvert}{Revenue}$
Nestle Canned Fruit Juice	2.05	-14.69	-12.65	1.20
Campbell Soup	0.76	-2.29	-1.54	0.39
Procter & Gamble	0.11	-4.32	-4.21	1.41
Dole	0.69	-1.47	-0.78	0.34
Nestle Canned Juice Drinks	-0.12	-0.69	-0.81	0.42
Citrus World	0.37	-1.13	-0.77	0.46
Texas Citrus Exchange	1.05	-1.51	-0.47	0.38
Empacadora de Frutas	-0.11	-0.52	-0.63	0.65

Note: Estimates are for the last month of the period (which ends January 31, 1999).