RAND Journal of Economics
Vol. 31, No. 3, Autumn 2000
pp. 395–421

Mergers with differentiated products: the case of the ready-to-eat cereal industry

Aviv Nevo*

Traditional merger analysis is difficult to implement when evaluating mergers in industries with differentiated products. I discuss an alternative, which consists of demand estimation and the use of a model of postmerger conduct to simulate the competitive effects of a merger. I estimate a brand-level demand system for ready-to-eat cereal using supermarket scanner data and use the estimates to (1) recover marginal costs, (2) simulate postmerger price equilibria, and (3) compute welfare effects, under a variety of assumptions. The methodology is applied to five mergers, two of which occurred and for which I compare predicted to actual outcomes.

1. Introduction

■ Traditional analysis of horizontal mergers is based primarily on industry-concentration measures. The market is defined and pre- and postmerger market shares of the relevant firms are used to compute pre- and postmerger concentration measures, which give rise to presumptions of illegality. Using this approach to evaluate mergers in industries with differentiated, or closely related but not identical, products is problematic. In many cases the product offerings make it difficult to define the relevant product (or geographic) market. Even if the relevant market can easily be defined, the computed concentration index provides a reasonable standard by which to judge the competitive effects of the merger only under strong assumptions.[1]

To deal with these challenges, a new methodology to evaluate mergers has been developed.[2] The basic idea consists of "front-end" estimation, in which demand functions and possibly supply relations are estimated, and a "back-end" analysis, in which the estimates are used to simulate the postmerger equilibrium. This article follows this

---

* University of California, Berkeley, and NBER; nevo@econ.berkeley.edu.

I wish to thank Gary Chamberlain, Richard Gilbert, Zvi Griliches, Michael Whinston, and various seminar participants, as well as the Editor, Rob Porter, and two anonymous referees, for comments and suggestions. I am grateful to Ronald Cotterill, the director of the Food Marketing Policy Center at the University of Connecticut, for sharing his data with me. Excellent research assistance was provided by Anita Lopez. Financial support from the University of California Committee on Research Junior Faculty Grant is gratefully acknowledged.

[1] For example, Willig (1991) uses the logit model to justify this practice. For issues in defining the relevant market, see Werden (1992, 1993), and in the context of differentiated-product industries, see Werden and Rozanski (1994), Vellturo (1997), and the references therein.

[2] See, for example, Baker and Bresnahan (1985), Berry and Pakes (1993), Hausman, Leonard, and Zona (1994), Werden and Froeb (1994, 1996), Baker (1997), Hausman and Leonard (1997), and Werden (1997).

methodology and uses it to evaluate actual and hypothetical mergers in the ready-to-eat (RTE) cereal industry. My general strategy is to model demand as a function of product characteristics, heterogeneous consumer preferences, and unknown parameters. I use data collected at supermarket checkout counters for 24 brands in 45 cities over 20 quarters to estimate a random-coefficients discrete-choice model of demand (McFadden, 1973, 1978, 1981; Cardell, 1989; Berry, 1994; Berry, Levinsohn, and Pakes, 1995). Building on the findings of Nevo (forthcoming), I use a Nash-Bertrand equilibrium assumption and the demand estimates to recover marginal costs. The recovered marginal costs and estimated demand parameters are used jointly to simulate the new equilibria that would result from several mergers under a variety of assumptions.

The ready-to-eat cereal industry is well suited for evaluating the performance of various methods for simulating the effects of mergers in differentiated-products industries. On September 1, 1992, General Mills, the second-largest producer of ready-to-eat cereal in the United States, announced its intent to purchase the Nabisco cereal line, at the time the sixth-largest producer. On November 4, General Mills called off the deal, citing antitrust concerns. Less than two weeks later, on November 17, Kraft, the owner of Post, the third-largest producer, announced its intent to buy the Nabisco cereal line. The acquisition was approved by federal authorities but challenged by the state of New York. During the trial, one of the major issues was whether the leading Nabisco brand, Shredded Wheat, and a leading Post brand, Grape Nuts, were the major competitors in a small submarket. The experts for the state claimed that this was true, and therefore the merger would significantly reduce competition. On the other hand, the experts for Kraft claimed there was sufficient competition from private labels and other brands to prevent the merged firm from increasing prices. Both sides used scanner data and econometric estimates to support their claims. After a lengthy trial, the merger was approved in February 1995.

On August 14, 1996, General Mills announced its intent to acquire the branded cereal line from Ralston Purina. The sale included the Chex line, Cookie Crisp, several other smaller brands that were later discontinued, and Chex Mix snacks. The revenue generated in 1995 by the products sold was roughly \$420 million, including \$80 million in Chex Mix sales. General Mills agreed to pay \$560 million. Since one of the motives for the sale was Ralston's goal of focusing on private labels, the agreement included a provision requiring that Ralston not be permitted to produce generic versions of Chex for two years after the sale. The merger was approved in December 1996.

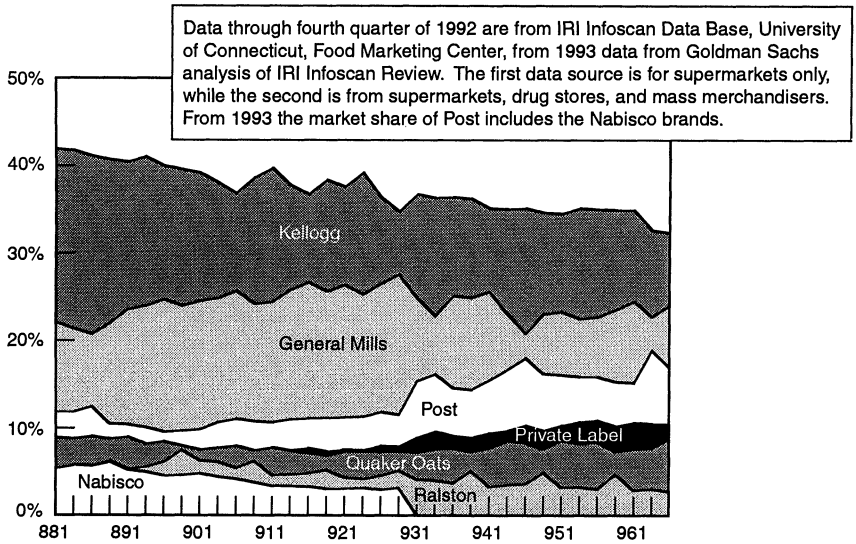
These, and two additional hypothetical mergers, are evaluated below. The analysis was performed without time pressure and using (almost) ideal premerger data. Time and data constraints might limit the ability to perform this analysis in real time.[3] Nevertheless, the analysis can be seen as answering the question of how well these methods perform without time constraints and (almost) ideal data. Using postmerger data I am able to partially evaluate the performance of the predictions and the sensitivity to the various assumptions. The results suggest that simulation of mergers is potentially useful, and the predictions of the model are fairly close to actual outcomes.

The rest of the article is organized as follows. Section 2 describes the history and current state of the ready-to-eat cereal industry. Section 3 presents the model used to simulate the effects of mergers. Data, estimation, and identifying assumptions are discussed in Section 4. Results are presented in Section 5, followed by a discussion in Section 6.

[3] In the case of the state of New York versus Kraft General Foods, Inc., similar analysis using even more detailed data was performed by both sides.

FIGURE 1

VOLUME MARKET SHARES



2. The ready-to-eat cereal industry

■ In 1997 the U.S. market consumed approximately 3 billion pounds of cereal, grossing roughly $9 billion in sales. Figure 1 shows the volume (pounds sold) market shares from 1988 through 1996. The three-firm concentration (C3) over this period decreases from 76% to 73%, while the six-firm concentration (C6) decreases from 95% to 85%.[4] This pattern is mirrored by a growth of private-label market shares.[5] The shift in shares of private labels had some impact on three of the mergers I analyze below. The decrease in market share of Shredded Wheat due to generic competition was probably one of the main factors that led Nabisco to sell its cereal line. On the other hand, the success of private labels gave Ralston, which sold its branded cereal business to General Mills, the ability to concentrate on the private-label cereal business.[6]

For economists, the concentration of the industry is troublesome because the industry leaders earn consistently high profits. This has drawn the attention of regulatory agencies to industry practices. Perhaps the best known case was the anticompetitive complaint brought by the U.S. Federal Trade Commission against the top three manufacturers—Kellogg, General Mills, and Post—in the 1970s. The focus of that specific complaint was one of the industry's key characteristics: an enormous amount of brands. Without counting negligible brands or market tests, there are currently over 200 brands available. Market shares at the brand level are fairly concentrated. The top 25 brands account for more than 55% of sales, while the top 50 brands account for roughly 85%.

Not only are there many brands in the industry, but, as Figure 2 shows, the rate at which new brands are introduced is high and has been increasing over time. The rate of new brand introduction peaked in the second half of the 1980s, with a sharp

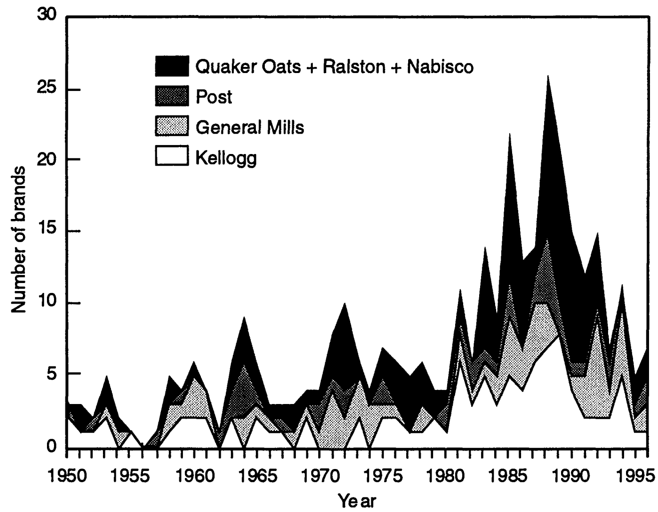
[4] During this period the Nabisco cereal line was bought by Post. Therefore, the definition of C3 is not completely consistent throughout this period, and C6 is really C5 at the end of the period.

[5] Private labels are brands sold under the retailer's own label. In this industry, unlike many other industries, these brands are not produced by the leading firms. The exception is Ralston.

[6] *Wall Street Journal,* September 1, 1992, page A2, and *The New York Times,* August 15, 1996, page D6.

FIGURE 2

NUMBER OF NEW CEREAL BRANDS INTRODUCED NATIONALLY BY TOP 6



drop in the beginning of the 1990s. This abrupt decline was partially due to a lack of attempts to introduce cereal to the national market. However, at least initially, it was mainly driven by a lack of success. Of the 28 brands introduced to test markets in 1988, 26 were later introduced nationally, while in 1989 and 1990 only 21 out of 29 and 15 out of 20 were introduced nationally. Of those brands that were introduced nationally, most did not survive in the long run. For example, of the 30 brands Kellogg introduced between 1985 and 1989, only 15 were still in production in 1994, while only 5 out of 15 introduced in 1980 through 1984 were in production.

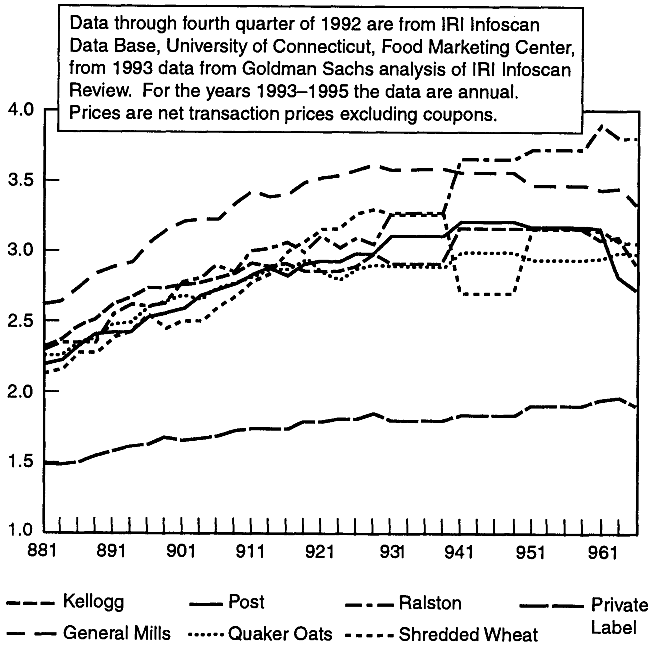
Trends in prices can be seen in Figure 3. In the five years from 1988 to 1992, average prices of cereal rose significantly. The average increase for the industry was roughly 35%, compared to a 21% increase in the consumer price index. The timing of the price increases is consistent with an attempt by the cereal manufacturers to obtain rents from the new brands introduced in the late 1980s.

Figure 3 illustrates an interesting pattern among the main brands in the Post-Nabisco merger and General Mills' acquisition of Chex. In the 2–3 years preceding the merger, price inflation was much higher for Shredded Wheat and Chex than the industry average. Between the second quarter of 1990 and the fourth quarter of 1992, when the Post-Nabisco merger was announced, the price of Shredded Wheat increased by 32%, compared to an average of 7%–12% for other companies. In the postmerger period, between the last quarter of 1992 and the third quarter of 1996, the price fell by 8%, which was comparable to trends among other brands. On the other hand, Chex's price increased 25% during this same period. One has to be careful in drawing conclusions from these facts, since many things happened during this period.

The rate of inflation slowed between 1993 and 1995. Whether causal or not, during this period the main change in market shares was the increase in the share of private-label cereals. On April 16, 1996, Kraft, owner of the Post and Nabisco cereal lines, announced a 20% price reduction on all its cereal brands. This was followed by similar announcements by Kellogg, General Mills, and Quaker Oats. The actual price changes offered to consumers were much smaller and ranged between 3%–7%.

FIGURE 3

AVERAGE PRICE PER POUND



All prices discussed above are net transaction prices excluding coupons. Because the number and value of coupons issued increased during the period 1988–1994, the above claims, for the most part, slightly overestimate the increase in prices paid by consumers. Economists usually think of coupons as tools to price discriminate. However, there are several interesting patterns in the use of coupons that suggest this is not the main motivation in this industry. Rather, the data seem to suggest that coupons are a marketing device (Nevo and Wolfram, 1999). An additional aspect of marketing, media advertising, has been an important dimension of competition in this industry since its origins. Advertising-to-sales ratios are currently approximately 13%, compared to 2–4% in other food industries.

3. The model

■ In this section I present a model of demand and supply to evaluate the competitive effects of the above mergers.[7] The essential idea is to estimate the structural parameters that govern demand and supply and use them to simulate the postmerger equilibrium. Here I estimate the demand system and use the estimated elasticities jointly with a model of supply to recover marginal costs. In principle, the supply relation could be estimated jointly with the demand system.

□ **Demand.** The first step in computing the effects of a merger, sometimes called the front end, is estimating demand. This step is not only the most difficult from an

[7] To the best of my knowledge, this idea was first proposed in this context by Baker and Bresnahan (1985). Except for small differences in the setup of demand, the model used here is identical to the one outlined by Berry and Pakes (1993).

econometric viewpoint, but is also a critical determinant of the outcome of the next several steps. Its importance parallels that of the market definition in traditional merger analysis. I focus on the model I use for the analysis below. Alternative methods will be discussed briefly later. However, a full empirical comparison of alternatives to the method used here is beyond the scope of this article. The interested reader is referred to Nevo (1997) for such a comparison.

Suppose we observe $t = 1, \ldots, T$ markets, each with $i = 1, \ldots, M_t$ consumers. In the estimation below a market will be defined as a city-quarter combination. The conditional indirect utility of consumer i from product j in market t is

$$u_{ijt} = x_{jt}\beta_i^* + \alpha_i^* p_{jt} + \xi_{jt} + \epsilon_{ijt} \equiv V_{ijt} + \epsilon_{ijt}, \qquad i = 1, \ldots, I_t, \quad j = 1, \ldots, J_t, \quad t = 1, \ldots, T, \tag{1}$$

where x_{jt} is a K-dimensional (row) vector of observable product characteristics, including national media advertising, p_{jt} is the price of product j in market t, ξ_{jt} is an unobserved (by the econometrician) product characteristic, and ϵ_{ijt} is a mean-zero stochastic term. Finally, $(\alpha_i^* \ \beta_i^*)$ are $K + 1$ individual-specific coefficients.

Examples of observed characteristics are calories, sodium, and fiber content. The unobserved characteristic includes market-specific effects of merchandising, other than national advertising. Formally, we can model the unobserved component as $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$. In the empirical application, ξ_j and ξ_t will be captured by brand and time dummy variables.[8] Market-specific components are included in $\Delta\xi_{jt}$ and are left as the econometric error term. I assume both firms and consumers observe the observed and unobserved (by the econometrician) product characteristics and take them into consideration when making decisions.

The specification given by equation (1) assumes that all consumers face the same product characteristics. This implies that the unobserved characteristic is identical for all consumers. Since the coefficient on price is allowed to vary among individuals, this is consistent with the theoretical literature of vertical product differentiation.[9] This specification also implies that all consumers in a market are offered the same price. In reality this will not be true: price varies between stores within a city and over time in a given store. Using an average price, as I do below, leads to measurement error and provides an additional motivation for the instrumental-variable procedure discussed below.

I model the distribution of consumers' taste parameters for the characteristics as multivariate normal (conditional on demographics) with a mean that is a function of demographic variables and parameters to be estimated, and a variance-covariance matrix to be estimated. Let

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \qquad v_i \sim N(0, I_{K+1}),$$

where K is the dimension of the observed characteristics vector, D_i is a $d \times 1$ vector of demographic variables, Π is a $(K + 1) \times d$ matrix of coefficients that measure how

[8] I abuse notation here. The index t refers to market (i.e., city-quarter) specific variables, while in the application I include only time dummy variables. I do this to avoid having to introduce an additional subscript.

[9] An alternative is to model the distribution of the valuation of the unobserved characteristics, as in Das, Olley, and Pakes (1994).

the taste characteristics vary with demographics, and Σ is a scaling matrix. This specification allows individual characteristics to consist of demographics that are "observed" and additional characteristics that are "unobserved," denoted D_i and v_i respectively.[10]

Specification of the demand system is completed with the introduction of an "outside good"; the consumers may decide not to purchase any of the brands. The indirect utility from this outside option is

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \epsilon_{i0t}.$$

I assume that consumers purchase one unit of the good that gives the highest utility. This implicitly defines the set of individual-specific variables that lead to the choice of good j. Formally, let this set be

$$A_{jt}(x_{.t}, p_{.t}, \xi_{.t}; \theta) = \{(D_i, v_i, \epsilon_{.t}) | u_{ijt} \geq u_{i\ell t} \ \forall \ \ell = 0, 1, \ldots, J\},$$

where $x_{.t}$, $\xi_{.t}$ and $p_{.t}$ are $J \times 1$ vectors of observed and unobserved characteristics and prices of all brands, and θ is a vector that includes all the parameters of the model. Assuming ties occur with zero probability, the market share of the jth product as a function of the mean utility levels of all the $J + 1$ goods, given the parameters, is

$$s_{jt}(x_{.t}, p_{.t}, \xi_{.t}; \theta) = \int_{A_{jt}} dP^*(D, v, \epsilon) = \int_{A_{jt}} dP^*_{\epsilon}(\epsilon)\, dP^*_{v}(v)\, dP^*_{D}(D), \qquad (2)$$

where $P^*(\cdot)$ denotes population distribution functions. The second equality is a consequence of an assumption of the independence of D, v, and ϵ. Even if only aggregate share data is observed, the model can be estimated by choosing the parameters that minimize the distance, in some metric, between the shares predicted by equation (2) and observed shares.

A comment is in order about the assumption that consumers choose no more than one brand. Taking the notation literally implies that consumers choose a single brand each quarter. If I allow i to capture not just different individuals but also the same consumer at different consumption spells during the quarter, then the model can be viewed as a consumer making several discrete decisions in a quarter and these decisions aggregated over time (not just across individuals). There are two potential problems with this interpretation. First, since many consumers purchase more than one brand of cereal in any supermarket trip, one could still question the discrete-choice assumption. However, most people consume only one brand of cereal at a time, which is the relevant fact for this modelling assumption. If mixing of several brands in a serving is not a negligible phenomenon, then the model can be viewed as an approximation to the true choice model. An alternative is to explicitly model the choice of multiple products, or continuous quantities (as in Dubin and McFadden (1984) or Hendel (1999)). Second, if multiple purchases are allowed by each consumer in a single quarter, then the assumption, discussed below, of the independence of ϵ_{ijt} across i is even more questionable. The full model allows for correlation across i, which enters through the

[10] The distinction between "observed" and "unobserved" individual characteristics refers to auxiliary datasets and not to the main data source, which includes only aggregate quantities and average prices. Below, the Current Population Survey will be used to sample from the empirical distribution of the "observed" characteristics.

demographic variables, and therefore adjusts for this problem in a reduced-form way (i.e., without modelling the effect directly).

Assuming that consumer heterogeneity enters the model only through the additive random shocks, ϵ_{ijt}, and that these shocks are identically and independently distributed with a Type I extreme-value distribution reduces the model to the multinomial logit model. Due to its tractability, the logit model has been used for simulating the effects of mergers (Werden and Froeb, 1994). However, the logit model greatly restricts the own- and cross-price elasticities (for details see McFadden (1981) or Berry, Levinsohn, and Pakes (1995)). Slightly less restrictive models, in which the identically and independently distributed assumption is replaced with a variance components structure, are available (the generalized extreme value model, McFadden (1978)). The nested logit model and the principles of differentiation generalized extreme value model (Bresnahan, Stern, and Trajtenberg, 1997) fall within this class.

The full model nests these other models and allows for flexible patterns of own- and cross-price elasticities. Cross-price substitution patterns will be driven by product characteristics and are not constrained by *a priori* segmentation of the market, yet at the same time can take advantage of this segmentation by including segment dummy variables as characteristics.

□ **Supply and equilibrium.** Suppose there are F firms, each of which produces some subset, $\mathcal{F}_f$, of the $j = 1, \ldots, J$ different brands. The profits of firm f are

$$\Pi_f = \sum_{j \in \mathcal{F}_f} (p_j - mc_j) M s_j(p) - C_f,$$

where $s_j(p)$ is the market share of brand j, which is a function of prices of all brands, M is the size of the market, mc_j is the constant marginal cost of production,[11] and C_f is the fixed cost of production. The market size defined here is different from that used in traditional analysis of mergers in that it includes the share of the outside good. This definition allows us to keep the market size fixed while still allowing the total quantity of products sold to increase (since such an increase will result in a decrease in the share of the outside good). Therefore, the analysis of a merger is less sensitive to the exact definition of market size.[12]

Assuming (1) the existence of a pure-strategy Bertrand-Nash equilibrium in prices and (2) that the prices that support it are strictly positive, the price, p_j, of any product j produced by firm f must satisfy the first-order condition

$$s_j(p) + \sum_{r \in \mathcal{F}_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0.$$

These J equations imply price-costs margins for each product. The markups can be solved for explicitly by defining

$$\Omega_{jr}^{pre}(p) = \begin{cases} -\partial s_j(p)/\partial p_r, & \text{if } \exists f\colon \{r, j\} \subset \mathcal{F}_f; \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

In vector notation, the first-order conditions become

[11] See Scherer (1982) for a justification of constant marginal cost.

[12] The analysis can be sensitive to the market definition in two ways. First, demand estimation could be influenced (Berry, 1994; Nevo, 2000); this is not the case for the results presented below. Second, as I discuss below, in simulation of postmerger equilibrium the inside and outside goods are treated differently.

$$s(p) - \Omega^{pre}(p)(p - mc) = 0.$$

This implies a markup equation and implied marginal costs

$$p - mc = \Omega^{pre}(p)^{-1}s(p) \Rightarrow mc = p - \Omega^{pre}(p)^{-1}s(p). \tag{4}$$

I use (4) in several ways. First, in the tradition of the new empirical IO (Bresnahan, 1989), I assume that marginal costs are not observed. Therefore, I use estimates of the demand system to compute the marginal costs implied by (4). These estimates of marginal costs rely on obtaining consistent estimates of the demand system and on the equilibrium assumption. For the application below I assume a Nash-Bertrand equilibrium based on Nevo (forthcoming) that finds margins predicted from a Nash-Bertrand equilibrium to match accounting margins better than do those from other behavioral models. Second, to simulate the postmerger equilibrium I use the same Nash-Bertrand equilibrium assumption as before. In principle, the analysis is not constrained to having the same model of firm conduct before and after the merger, nor is it restricted to the one presented here.

Let Ω^{post} be a matrix defined by (3) using the postmerger structure of the industry. The predicted postmerger equilibrium price, p^*, solves

$$p^* = \widehat{mc} + \Omega^{post}(p^*)^{-1}s(p^*), \tag{5}$$

where $\widehat{mc}$ are the marginal costs implied by the demand estimates and the premerger ownership structure.

Equation (5) makes several nontrivial assumptions. First, it assumes a particular model of premerger conduct, Nash-Bertrand. If premerger behavior is more collusive than this assumption, I would overestimate marginal costs and the anticompetitive effects of a merger. The latter could be examined when comparing predicted to actual postmerger outcomes.

Second, I assume that the cost structure stays the same before and after the merger. Many mergers are justified on the basis of cost efficiency, which in some cases translates into a claim that marginal costs go down after the merger. Here I assume not only that production cost is constant but also manufacturer-retail relations, since the retailer markup is a part of the marginal cost. If one is willing to quantify the change in marginal costs due to the merger, then $\widehat{mc}$ can be adjusted appropriately. Such an adjustment can be based on an engineering estimate or econometric analysis, and it would allow us to translate the projected cost improvements into changes in equilibrium prices and quantities. Furthermore, we could ask the reverse question: How large do the cost improvements have to be in order to offset any anticompetitive effects of the merger? Are such costs reductions reasonable?

Third, the matrices Ω^{pre} and Ω^{post} use the same demand estimates and differ only in ownership structure. This does not imply that price elasticities are the same before and after the merger, since elasticity might vary with price. However, this approach is not consistent with firms changing their strategies in other dimensions that may influence demand. For example, if as a result of the merger the level of advertising changes, and advertising influences price sensitivity, then the estimate of the postmerger equilibrium price based on (5) will be wrong. In addition this implies that characteristics, observed and unobserved, and the value of the outside good are assumed to stay the same pre- and postmerger. Therefore, I am implicitly assuming that the price of the outside good is exogenous and does not change in response to the merger.

□ **Consumer welfare.** One of the advantages of the structural model is that it can be used not just to simulate the new equilibrium, but also to analyze the change in consumer welfare. A measure of the change is the compensating variation. If the marginal utility of income is fixed for each individual (i.e., it does not vary as a result of the price change),[13] then McFadden (1981) and Small and Rosen (1981) show that the compensating variation for individual i is given by

$$CV_i = \frac{\ln\left[\sum_{j=0}^{J} V_{ij}^{post}\right] - \ln\left[\sum_{j=0}^{J} V_{ij}^{pre}\right]}{\alpha_i^*}, \tag{6}$$

where V_{ij}^{pre} and V_{ij}^{post} are defined by (1) using the premerger prices and postmerger predicted prices, respectively. The mean compensating variation in the population is given by

$$M \int CV_i \, dP_D^*(D) \, dP_v^*(v), \tag{7}$$

where M is the total number of consumers and $P^*(\cdot)$ are distribution functions.

When computing changes in welfare, two assumptions have to be made about parts of the model that were not fully characterized. First, an assumption about changes in unobserved characteristics is required. A natural assumption is that, as with the observed characteristics, there is no change in the unobserved components, ξ_{jt}, at least in the short run. Second, I also assume that there are no changes in the utility from (or quality of) the outside good. Both assumptions are made in order to generate the postmerger equilibrium.

4. Data and estimation

■ **The data.** The data required to consistently estimate the model include the following variables: market shares and prices in each city-quarter, brand characteristics, advertising, and information on the distribution of demographics.

Market shares and prices were obtained from the IRI Infoscan Data Base at the University of Connecticut. Variable definitions and the details of data construction are given in Appendix A. These data are aggregated by brand (for example, different-sized boxes are considered one brand), city, and quarter. The sample covers 24 brands in 45 cities and ranges from the first quarter of 1988 to the last quarter of 1992. The combined city-level market share of brands in the sample varies between 42% and 63% of the total volume of cereal sold in each city and quarter. Combined national market shares vary between 55% and 60%. Although this sample leaves out many brands, those most relevant for the mergers analyzed below are included.

Summary statistics for the main variables are provided in Table 1. The last three columns show the percentage of variance due to brand, city, and quarter dummy variables. Controlling for the variation between brands, much of the variation in prices is due to differences across cities. The variation in prices is due to both exogenous and endogenous sources (i.e., variation correlated with demand shocks). Consistent estimation will have to separate these effects. The Infoscan price and quantity data were

[13] If the marginal utility of income varies, then the computation is more complex (McFadden, 1995).

TABLE 1 Prices and Market Shares of Brands in Sample

Description	Mean	Median	Standard Deviation	Minimum	Maximum	Brand Variation	City Variation	Quarter Variation
Prices (cents per serving)	20.1	18.8	6.0	7.6	43.4	92.3%	2.9%	1.2%
Advertising ($ million per quarter)	3.67	3.28	2.15	0	9.95	58.0%	—	2.6%
Share within cereal market (%)	2.2	1.8	1.5	.1	11.4	78.8%	.5%	.3%

Source: IRI Infoscan Data Base, University of Connecticut, Food Marketing Center.

matched with information on advertising, product characteristics, and the distribution of individual demographics obtained from the Current Population Survey (CPS); see Appendix A for details.

□ **Estimation.** I estimate the parameters of the model described in Section 3 using the data described in the previous subsection by following Berry (1994) and Berry, Levinsohn, and Pakes (1995). The key point of the estimation is to exploit a population moment condition that is a product of instrumental variables and a (structural) error term to form a (nonlinear) GMM estimator. The error term is defined as the unobserved product characteristics, ξ_{jt}. The main technical difficulties in the estimation are the computation of the integral defining the market shares, given in equation (2), and the inversion of the market share equations to obtain the error term (which can be plugged into the objective function). Some details of the estimation are given in Appendix A. For more details see Berry, Levinsohn, and Pakes (1995) or Nevo (2000).

□ **Instruments.** The key identifying assumption in the estimation is the population moment condition, detailed in Appendix A, which requires a set of exogenous instrumental variables. Prices are a function of marginal costs and a markup term. Once brand dummy variables are included in the regression, the error term is the unobserved city-quarter deviation from the overall mean valuation of the brand, denoted $\Delta\xi_{jt}$. I assume that firms observe and account for this deviation, which will influence the market-specific markup and will be correlated with prices. Therefore, (nonlinear) least-squares estimates will be biased and inconsistent.

I use an approach similar to that of Hausman (1996) and exploit the panel structure of the data. The identifying assumption is that, controlling for brand-specific means and demographics, city-specific valuations are independent across cities (but may be correlated within a city). Given this assumption, prices of the brand in other cities are valid instrumental variables since prices of brand j in any two cities (1) will be correlated due to the common marginal cost but (2) will be, due to the independence assumption, uncorrelated with market-specific valuation. One could use prices in all other cities and quarters as instruments. I use regional quarterly average prices (excluding the city being instrumented) in all twenty quarters.

There are several plausible situations in which the independence assumption will not hold. I discuss several of them in Appendix B. In addition to providing arguments supporting the validity of the instrumental variables, I compare the estimates to those obtained from direct proxies for marginal costs. The comparison can only be done in the context of the more restrictive logit model. The results, presented in Appendix B, demonstrate that the estimates obtained from the different identifying assumptions are essentially identical.

5. Results

■ This section simulates price changes that would result from mergers in the ready-to-eat cereal industry. Five mergers and acquisitions are examined. First, I analyze Post's acquisition of the Nabisco cereal line and General Mills' acquisition of Chex. Next, I simulate the effects of the proposed purchase of Nabisco cereals by General Mills, which was called off due to antitrust concerns. Finally, I examine two hypothetical mergers: Quaker Oats with Kellogg and Quaker Oats with General Mills. The choice of these two is intended only to demonstrate how the model works.

□ **Demand.** Results of the demand estimation are presented in Table 2. The first column displays the means of the taste parameters, α and β. The next five columns

TABLE 2 **Results from Mixed Logit Model**

			Interactions with Demographic Variables:			
Variable	Means (β's)	Standard Deviations (σ's)	log(Income)	log(Income)^2	Age	Child
Price	−43.039	.339	761.747	−41.637	—	−3.053
	(11.015)	(2.119)	(214.241)	(11.799)		(4.181)
Advertising	.030	—	—	—	—	—
	(.009)					
Constant	−2.685[a]	.095	2.331	—	.4586	—
	(.135)	(.649)	(2.601)		(.650)	
Cal from fat	1.661[a]	3.396	—	—	—	—
	(.261)	(2.713)				
Sugar	18.540[a]	.845	−45.439	—	7.302	—
	(.994)	(6.337)	(14.616)		(3.978)	
Mushy	.938[a]	.348	11.322	—	1.193	—
	(.268)	(.922)	(2.435)		(.824)	
Fiber	−2.898[a]	2.036	—	—	—	−14.685
	(.445)	(4.520)				(5.866)
All-family	1.237[a]	.216	—	—	—	
	(.134)	(1.496)				
Kids	−2.539[a]	1.739	—	—	—	
	(.276)	(.740)				
Adults	3.788[a]	1.959	—	—	—	
	(.441)	(.862)				
GMM objective (degrees of freedom)				1.60 (8)		
Minimum distance χ^2 (degrees of freedom)				148 (16)		
Minimum distance weighted R^2				.51		
% of price coefficients >0				0		

Number of observations is 21,600. Except where noted, parameters are GMM estimates. All regressions include brand and time dummy variables. Robust standard errors are given in parentheses.

[a] Estimates from a second-stage minimum distance projection of the estimated brand fixed effects onto product characteristics.

present the parameters that measure heterogeneity in the population: standard deviations, interaction with log of income, the squared log of income, log of age, and a dummy variable equal to one if age is less than sixteen. The means of the distribution of marginal utilities, β's, are estimated by a minimum distance procedure (see Appendix A for details). All coefficients are statistically significant. For the average consumer, sugar has positive marginal utility, while fiber has a negative marginal utility.

Estimates of standard deviations of taste parameters are not significant at conventional significance levels for all characteristics except for the *Kids* and *Adults* segment dummy variables. Most interactions with demographics are significant. Marginal utility from sugar decreases with income, whereas the marginal valuation of sogginess increases with income. These results are similar to those presented in Nevo (forthcoming), which contains a detailed discussion of the results and the economic implications.

The results suggest that individual price sensitivity is heterogenous. The estimate of the standard deviation is not statistically significant, suggesting that most of the heterogeneity is explained by the demographics. Price sensitivity is not monotonic in income. Consumers with average income tend to be the least price sensitive. Households with children are statistically not more sensitive. Allowing the price coefficient to be a nonlinear function of income is important (Nevo, forthcoming). Further nonlinearity was explored by adding additional powers of income, which in general were found to be nonsignificant.

Table 3 presents a sample of elasticities implied by the results. The model does not restrict the elasticities to be the same across markets. Therefore, rather than presenting the elasticities for a particular market, I display the medians across the 900 city-quarter combinations. I note that the two problems of the logit model, found in the results displayed in Appendix B, are not present here. The own-price elasticities are not linear in price, despite the fact that price enters utility in a linear form. This is due to the heterogeneity in price sensitivity. Consumers who purchase different products have different price sensitivity. In addition, substitution patterns across brands are driven by product characteristics.

□ **Additional specifications and sensitivity analysis.** The results presented in the previous section relied on several key assumptions, which I now examine. First, I examine the identifying assumption made to justify the instrumental variables. Appendix B displays some results that support the use of these instrumental variables. Second, I explore the sensitivity of the results to definitions of key variables (for example, the share of the outside good), functional form (mainly in the interaction with demographics), and distributional assumptions. The results presented here were found to be robust (and can be found for a slightly different dataset in Nevo (forthcoming)).

Third, I compare the results to the main alternative method, a multilevel demand system (Hausman, Leonard, and Zona, 1994; Hausman, 1996). A comparison of the two methods has both methodological and practical interest because these methods have been used to evaluate some recent mergers. A full comparison is beyond the scope of this article but can be found in Nevo (1997). Using the same dataset I find that the multilevel demand system yields, for this industry, somewhat disturbing cross-price elasticities. Some of the cross-price elasticities are estimated to be negative. This "wrong" sign occurs most often for products commonly viewed as close substitutes. For example, Post Raisin Brand and Kellogg's Raisin Bran appear to be complements. If used in the analysis below, this would yield strange results. For example, if Post and Kellogg merged, the price of both firms' Raisin Bran would be predicted to decrease.

TABLE 3 Median Own and Cross-Price Elasticities

#	Brand	K Corn Flakes	K Raisin Bran	K Frosted Flakes	K Rice Krispies
1	K Corn Flakes	−3.696	.023	.500	.010
2	K Raisin Bran	.023	−2.061	.088	.051
3	K Frosted Flakes	.361	.059	−3.546	.028
4	K Rice Krispies	.010	.048	.040	−1.320
5	K Frosted Mini Wheats	.000	.053	.003	.057
6	K Froot Loops	.000	.010	.008	.038
7	K Special K	.155	.072	.248	.039
8	K NutriGrain	.270	.094	.313	.023
9	K Crispix	.003	.038	.020	.079
10	K Cracklin Oat Bran	.000	.023	.001	.046
11	GM Cheerios	.007	.080	.035	.069
12	GM Honey Nut Cheerios	.001	.017	.017	.043
13	GM Wheaties	.503	.113	.445	.029
14	GM Total	.140	.064	.238	.042
15	GM Lucky Charms	.000	.012	.010	.041
16	GM Trix	.000	.010	.009	.043
17	GM Raisin Nut	.007	.137	.043	.059
18	P Raisin Bran	.014	.232	.063	.050
19	P Grape Nuts	.001	.048	.006	.050
20	Q 100% Natural	.000	.023	.002	.048
21	Q Life	.003	.038	.052	.048
22	Q CapNCrunch	.001	.013	.015	.038
23	R Chex	.005	.037	.028	.081
24	N Shredded Wheat	.002	.081	.018	.049
25	Outside good	.158	.036	.107	.036

Cell entries i, j, where i indexes row and j column, give the percent change in market share of brand i with a 1% change in price of j. Each entry represents the median of the elasticities from the 900 markets. K = Kellogg, GM = General Mills, P = Post, Q = Quaker Oats, R = Ralston, N = Nabisco.

This phenomenon is not limited just to my data. It appears also in Hausman (1996). This result may, however, be due to idiosyncracies of the cereal industry, since it does not seem to happen in the studies of Hausman, Leonard, and Zona (1994) and Ellison et al. (1997). It is my conjecture that this is due to a partial failure of the instrumental variables. Demand at the bottom level of the multilevel system is estimated by regressing quantities (expenditure shares) on prices of all brands in that segment. This requires that the instrumental variables have sufficient variation across brands in order to precisely estimate the effects of prices of all close competitors. For very close substitutes, prices in all markets are likely to move jointly (either due to strategic effects or common cost and demand shocks). Since the instrumental variables I use are prices in other cities, they are likely to be highly correlated across brands. Therefore, the instrumental

TABLE 3 *Extended*

GM Cheerios	GM Lucky Charms	P Raisin Bran	P Grape Nuts	Q Life	R Chex	Shredded Wheat
.011	.000	.007	.000	.000	.002	.001
.131	.008	.110	.030	.011	.012	.032
.040	.004	.021	.003	.008	.006	.005
.106	.025	.023	.030	.033	.024	.018
.102	.034	.032	.054	.044	.015	.023
.043	.111	.006	.024	.163	.010	.008
.054	.002	.025	.019	.004	.009	.028
.046	.001	.034	.011	.002	.004	.022
.103	.027	.019	.032	.035	.024	.018
.103	.040	.014	.039	.058	.012	.011
−1.709	.020	.041	.037	.028	.021	.024
.055	.099	.009	.026	.142	.012	.010
.054	.001	.041	.003	.002	.005	.007
.059	.003	.022	.020	.005	.010	.027
.049	−1.945	.007	.026	.149	.011	.009
.052	.102	.006	.024	.141	.012	.009
.160	.012	.065	.029	.019	.016	.026
.134	.009	−2.030	.036	.012	.011	.034
.089	.025	.026	−2.096	.032	.013	.070
.103	0.42	.013	.036	.063	.013	.011
.080	.072	.019	.028	.103	.014	.015
.048	.105	.007	.023	−1.559	.010	.008
.106	.024	.017	.027	.031	−1.749	.017
.099	.015	.043	.115	.020	.014	−2.268
.048	.017	.016	.017	.030	.009	.010

variables are unlikely to have enough variation, across close substitutes, to separate the effects of own price and prices of close substitutes. In the discrete-choice framework I rely on theory to derive an estimation equation, which includes only own price and not the prices of other substitutes, therefore relaxing some of the requirements from the instrumental variables.

□ **Marginal costs.** Marginal costs are recovered by assuming a premerger Nash-Bertrand equilibrium, as described in Section 3. This procedure makes several strong assumptions, which were previously discussed. Below I examine some of the implications of these assumptions. Predicted marginal costs are displayed in Table 4. Marginal cost is defined, in this context, as the cost to the manufacturer of getting a box of cereal to the shelf. It includes transportation costs from the plant to the supermarket, the retailer's cost, and markup. Therefore, these predicted costs will

TABLE 4 Predicted Marginal Costs

	Median Premerger Price (¢ per serving)	Median Marginal Cost (¢ per serving)		Margin $(p - mc)/p$	
		Logit	Mixed Logit	Logit	Mixed Logit
K Corn Flakes	9.8	3.1	6.5	68.5%	34.8%
K Raisin Bran	17.3	10.7	7.4	38.1%	57.4%
K Frosted Flakes	14.8	8.3	9.8	44.2%	31.9%
K Rice Krispies	13.1	6.5	1.8	50.4%	85.8%
K Frosted Mini Wheats	28.0	21.4	14.7	23.7%	46.7%
K Froot Loops	18.3	11.7	8.7	36.4%	52.4%
K Special K	20.7	14.1	14.5	31.7%	32.5%
K NutriGrain	18.0	11.4	12.0	36.4%	33.4%
K Crispix	19.3	12.6	5.8	34.3%	68.1%
K Cracklin Oat Bran	37.0	30.3	23.4	18.0%	36.7%
GM Cheerios	18.8	12.5	6.7	34.0%	63.9%
GM Honey Nut Cheerios	17.4	11.0	5.9	36.7%	64.9%
GM Wheaties	15.6	9.3	11.8	40.9%	24.0%
GM Total	22.2	15.8	16.4	28.7%	25.9%
GM Lucky Charms	20.2	13.8	8.5	31.8%	56.9%
GM Trix	23.0	16.7	9.9	27.8%	56.6%
GM Raisin Nut	32.8	26.4	21.3	19.6%	36.3%
P Raisin Bran	17.8	11.7	9.0	34.3%	48.9%
P Grape Nuts	23.6	17.5	13.5	25.8%	43.8%
Q 100% Natural	26.1	19.9	14.4	23.6%	46.1%
Q Life	15.6	9.5	4.8	39.2%	69.8%
Q CapNCrunch	14.9	8.7	5.4	41.2%	61.7%
R Chex	19.7	13.6	8.6	30.7%	57.4%
N Shredded Wheat	27.5	21.5	16.6	21.9%	39.2%

Prices and marginal costs are the median for each brand over the 45 cities in the last quarter of 1992. Mixed logit results are based on Table 2, while logit results are based on Appendix B. K = Kellogg, GM = General Mills, P = Post, Q = Quaker Oats, R = Ralston, N = Nabisco.

vary by market (city-quarter combination). Rather than displaying the predicted costs for a particular market, I present the median cost for each brand across the 45 cities in the last quarter of 1992.[14]

The results for the logit model are based on the estimates in Appendix B. The restrictive form of the logit model implies that the markup is equal for all brands of the same firm. This yields somewhat unrealistic patterns of marginal costs. The full model allows for heterogeneity in the marginal valuation of the brands and therefore frees the restrictions that cause this behavior. Indeed, most of the costs predicted by

[14] Means are essentially identical. I display medians to eliminate sensitivity to outliers.

the mixed logit model are reasonable. The following patterns can be observed. (1) Brands that we think are cheaper to produce have lower costs. For example, Kellogg's Corn Flakes is slightly cheaper to get to shelf than Kellogg's Frosted Flakes (Frosted Flakes are essentially Corn Flakes coated with frosting). (2) Similar brands of companies with larger market shares, and potentially more bargaining power with retailers, have lower costs. For example, Kellogg's Raisin Bran is cheaper to get to shelf than Post Raisin Bran[15] and Kellogg's Crispix is cheaper than Chex. (3) Holding price constant, brands with larger shares have lower costs, which is consistent with retailers using lower markups on the larger brands due to their power to attract consumers to the store. Alternatively, due to shorter shelf life, inventory costs are lower per box for the larger brands. (4) Kids' cereals tend to have higher markups and lower predicted costs, which is consistent both with production costs and retailer behavior. (5) Kellogg's Rice Krispies is an outlier in its predicted costs. The demand model predicts a high markup for this brand, and because its price is relatively low the result is a low predicted marginal cost. There are several potential explanations, including misspecification of the demand system, but since the simulations below are not affected, I do not explore this matter further.

□ **Postmerger equilibrium.** The postmerger equilibrium is simulated using the demand estimates and the recovered marginal costs. I present results, first, under the assumption that marginal costs are the same before and after the merger. Next, I explore the effects of cost reductions. All computations are based on the demand estimates presented in Table 2. The postmerger equilibrium is computed for each of the 45 cities in the sample using data of the last quarter of 1992. Table 5 presents the percentage increase in equilibrium prices and quantities assuming no cost reduction. I present in Table 6 the cost reductions required to leave the equilibrium price unchanged. This last set of results is useful because in many cases it is hard to predict the actual cost reduction. Therefore, it might be useful to ask: What magnitude of cost efficiencies would leave the equilibrium outcome unchanged?

The first merger I analyze is Post's acquisition of the Nabisco cereal line. The main argument of New York State officials was that the high degree of substitution between Post Grape Nuts and Nabisco Shredded Wheat would lead to an increase in the price of these products if the merger were to occur. Merger simulation results are presented in the first column of Table 5. Despite the prediction that Grape Nuts is the closest substitute for Shredded Wheat (Table 3), the simulated price increases are low. The point estimates are a 3.1% and 1.5% price increase for Shredded Wheat and Grape Nuts, respectively.[16,17] If I assume a 5% decrease in marginal cost of Post and Nabisco brands, then the effects of the merger are offset. Given the small production scale of Nabisco before the merger and the estimates of marginal costs presented in the previous section, a 5% cost reduction is not completely unreasonable.

The second merger simulated is the attempt of General Mills to acquire the Nabisco cereal line, before the purchase by Post. The acquisition was cancelled due to antitrust concerns. Indeed, the simulated price increase for Shredded Wheat is 7.5% (with a

[15] For these two brands there is potentially another factor. Many raisin bran consumers claim that Post's version has more raisins. I did not examine this claim directly; however, a serving of Post Raisin Bran has more sugar and is higher in fiber, which is consistent with this claim.

[16] To construct confidence intervals for the point estimates presented in Tables 5 through 7, I use a parametric bootstrap. I draw parameter values from a normal distribution with mean and variance equal to the estimates in Table 2. For each of these draws I calculate the predicted price increase.

[17] For the Post-Nabisco merger, the 95% confidence intervals for the price increase of Shredded Wheat and Grape Nuts are [1.6, 4.8] and [.6, 2.2], respectively.

TABLE 5 **Predicted Percent Change in Prices and Quantities as a Result of Mergers**

	Post and Nabisco		GM and Nabisco		GM and Chex		Kellogg and Quaker Oats		GM and Quaker Oats	
	p	q	p	q	p	q	p	q	p	q
K Corn Flakes	.0	.0	.0	.1	.0	.1	.0	.5	.0	.3
K Raisin Bran	.1	.1	.1	.3	.1	.2	1.4	−1.7	.5	.7
K Frosted Flakes	.0	.0	.0	.1	.0	.1	.3	−.4	.1	.3
K Rice Krispies	.0	.1	.1	.2	.1	.4	5.1	−4.1	.7	2.0
K Frosted Mini Wheats	.0	.2	.0	.2	.1	.3	2.7	−4.1	.3	2.9
K Froot Loops	.0	.1	0	.2	.1	.5	9.3	−15.3	.7	8.0
K Special K	.0	.1	.1	.2	.0	.2	.2	.2	.1	.4
K NutriGrain	.0	.0	.1	.1	.0	.1	.0	.4	.1	.3
K Crispix	.0	.1	.0	.2	.1	.4	3.4	−3.8	.5	2.7
K Cracklin Oat Bran	.0	.1	.0	.2	.0	.4	3.4	−6.8	.4	3.7
GM Cheerios	.0	.2	.7	−.9	1.1	−1.3	.5	1.3	4.1	−3.5
GM Honey Nut Cheerios	.0	.1	.5	−.6	.8	−.9	1.0	3.2	11.5	−11.2
GM Wheaties	.0	.0	.0	0	.1	−.1	.1	.5	.1	.3
GM Total	.0	.1	.3	−.8	.2	−.6	.1	.4	.2	.1
GM Lucky Charms	.0	.1	.3	−.4	.7	−.8	.8	3.3	9.3	−10.6
GM Trix	.0	.1	.3	−.3	.7	−.9	.7	3.5	8.6	−9.6
GM Raisin Nut	.0	.2	.4	−.7	.5	−.9	.3	1.5	1.8	−2.7
P Raisin Bran	.9	−1.5	.0	.5	.0	.4	.1	1.5	.2	1.7
P Grape Nuts	1.5	−2.8	.1	.7	.0	.4	.1	2.3	.1	3.0
Q 100% Natural	.0	.1	.0	.3	.0	.5	10.2	−17.0	11.4	−19.3
Q Life	.0	.1	.0	.3	.1	.5	15.5	−16.7	23.8	−25.3
Q CapNCrunch	.0	.1	.0	.3	.1	.4	16.8	−16.7	29.1	−30.9
R Chex	.0	.2	.0	.3	12.2	−19.0	.0	2.1	.1	3.4
N Shredded Wheat	3.1	−8.6	7.5	−18.8	.0	.4	.0	1.9	.0	2.5

Figures are the median change for each brand over the 45 cities in the last quarter of 1992, and are based on Table 2.

95% confidence interval of between 4.0 and 13.1). A 5% cost reduction is no longer enough to offset the effects of the merger. As seen in the second column of Table 6, the cost reduction to Shredded Wheat would need to be greater than 10% (with a 95% confidence interval of between 5.1 and 21.4) in order to reach the same equilibrium outcome.

In August 1996 General Mills purchased from Ralston the Chex cereal line. This merger was examined by the federal authorities and not challenged. The increase in price is presented in the third column of Table 5.[18] The predicted price increases and

[18] The results presented here take the premerger state as prior to the Post-Nabisco merger. I also tried to simulate these mergers sequentially, i.e., take into account that Post acquired the Nabisco cereal line when computing the premerger stats. The results were essentially the same.

TABLE 6 **Percent Reduction in Marginal Costs Required for No Change in Predicted Postmerger Prices**

	Post and Nabisco	GM and Nabisco	GM and Chex	Kellogg and Quaker Oats	GM and Quaker Oats
K Corn Flakes	0	0	0	.2	0
K Raisin Bran	0	0	0	4.0	0
K Frosted Flakes	0	0	0	1.0	0
K Rice Krispies	0	0	0	16.5	0
K Frosted Mini Wheats	0	0	0	5.2	0
K Froot Loops	0	0	0	17.4	0
K Special K	0	0	0	.6	0
K NutriGrain	0	0	0	.5	0
K Crispix	0	0	0	13.2	0
K Cracklin Oat Bran	0	0	0	5.4	0
GM Cheerios	0	2.1	3.4	0	12.1
GM Honey Nut Cheerios	0	1.2	2.3	0	29.7
GM Wheaties	0	.1	.2	0	.4
GM Total	0	.6	.4	0	.6
GM Lucky Charms	0	.9	1.6	0	19.2
GM Trix	0	.7	.1.5	0	17.3
GM Raisin Nut	0	.7	.8	0	3.7
P Raisin Bran	1.7	0	0	0	0
P Grape Nuts	2.6	0	0	0	0
Q 100% Natural	0	0	0	16.8	20.1
Q Life	0	0	0	46.9	72.2
Q CapNCrunch	0	0	0	29.1	42.5
R Chex	0	0	22.1	0	0
N Shredded Wheat	5.1	10.4	0	0	0

Figures are based on Table 2.

the reductions in marginal costs required to offset the anticompetitive effects are larger than in the previous two mergers. A 12.2% price increase is predicted for Chex (with a 95% confidence interval of between 7.9 and 28.0). For this merger there were other considerations that could have counterbalanced the price increase. For example, Ralston's goal was to concentrate on its private-label business, which might thereby check the price increase of branded cereal. In the simulation this effect is not incorporated, as the outside good does not change.

The last two mergers considered are between Quaker Oats (or its three brands in the sample) and either Kellogg or General Mills. Both of these are hypothetical mergers and are used only to demonstrate the method proposed here. The results from these thought experiments can be seen in the last two columns of Tables 5 and 6.

The results in Tables 5 and 6 demonstrate the effect of a merger on prices. However, they do not give any criteria by which to judge if these price changes are large

TABLE 7 **Change in Variable Profits and Consumer Surplus as a Result of Mergers (millions of dollars per year)**

	Post and Nabisco		General Mills and Nabisco	
Consumer surplus	−13.98		−26.79	
Profits/revenues (total)	6.20	−4.77	10.66	−12.33
Kellogg	2.56	3.77	5.54	7.57
General Mills	2.34	3.65	2.63	−7.50
Post	.60	−5.17	1.54	2.94
Quaker Oats	.54	.84	1.43	2.07
Ralston	.14	.25	.30	.52
Nabisco	.01	−8.11	−.77	−17.93
Total Welfare	−7.78		−16.13	
Cost reduction (so total welfare is unchanged)	1.5%		10.8%	
Profits/revenues (total)	8.29	−1.81	16.89	−3.36
Kellogg	1.39	1.90	3.77	4.93
General Mills	1.35	1.92	.47	−13.46
Post	3.73	−.57	.65	1.18
Quaker Oats	.31	.43	1.12	1.58
Ralston	.09	.15	.20	.36
Nabisco	1.42	−5.65	10.68	2.07

The top half of the table is based on the results of Table 5. The bottom half displays the cost reductions required to keep total welfare unchanged, i.e., change in consumer surplus minus change in variable profits equals zero. The first three columns assume a fixed proportional reduction only to brands of acquired firm, while the last two columns assume cost reductions to brands of both firms.

or not. The right measure by which to answer this question is the influence of the merger on consumer welfare. In Table 7 I present changes in consumer surplus, profits, revenues, and total welfare assuming no cost reductions. I also present the breakdown in profits and revenues assuming the cost reductions keep total welfare unchanged.[19] Compensating variation, CV_i, is computed for each individual, in a sample taken from the CPS, by using equation (6). I average the compensating variation, CV_i, across the sample and multiply by the number of consumers, M in equation (7), to get total change in consumer surplus. The number of consumers is assumed to be 260 million (U.S. consumers) times 365 days.[20]

The results suggest that the Post-Nabisco merger, which was approved, has the smallest impact on consumer surplus and total welfare, approximately a reduction of \$14 and \$7 million a year, respectively (with 95% confidence intervals of between 7.0 and 27.2 million, and 1.0 and 16.7 million). The General Mills–Nabisco merger, which was not approved, would have had a higher impact on welfare. The General Mills

[19] Unlike the case examined in Table 6, the cost reductions are not unique. I assume that marginal costs were reduced by a fixed proportion for all brands of either the acquired firm (first three mergers) or both firms (last two mergers).

[20] Prices are all taken for a daily serving. Therefore, I have to multiply by the number of days to get annual aggregate demand and change in consumer surplus.

TABLE 7 *Extended*

General Mills and Chex		Kellogg and Quaker Oats		General Mills and Quaker Oats	
−43.70		−189.56		−288.64	
12.08	−2.35	62.93	9.67	95.97	27.15
6.17	8.66	13.66	−28.27	48.06	75.81
3.47	−4.68	39.71	58.15	35.70	−14.52
.98	1.86	4.75	9.12	7.17	14.20
2.19	3.28	1.79	−23.51	.01	−58.59
−1.07	−12.27	1.73	2.97	2.90	4.92
.33	.80	1.29	3.20	2.13	5.33
−31.62		−126.63		−192.67	
27.7%		5.3%		9.8%	
21.93	−.19	122.32	94.79	171.93	138.69
3.25	4.64	81.85	91.24	12.99	13.99
−.26	−13.48	26.07	23.78	138.72	161.71
.56	1.06	2.66	4.15	3.98	6.43
1.48	2.24	9.84	−27.76	13.32	−48.15
16.73	4.94	1.20	1.93	1.81	2.72
.17	.41	.72	1.45	1.11	1.98

acquisition of Chex generated an even greater reduction in consumer surplus and total welfare, \$44 and \$32 million, respectively,[21] yet was approved. In this acquisition there were several nonprice dimensions of competition that my model ignores, but they were important for this merger and could therefore reduce the impact on total welfare. I return to this point below. The last two mergers considered would have a substantial impact on total welfare, with a reduction of \$127 and \$193 million a year. These numbers are probably a lower bound on the true impact, because in these two mergers, unlike the previous mergers considered, several important brands of the merging firms are not included in the analysis.

The cost reductions required to keep consumer welfare fixed are monotonic in the original reduction in total welfare for the first three mergers. For these mergers, since there is a difference in the scale of production between the acquiring and acquired firm, it makes sense to assume that only the smaller, acquired, firm's brands will enjoy cost reductions. For the last two mergers I define the cost reductions differently. I assume that all brands of both merging firms enjoy the same percentage reduction. An alternative is to assume that only the Quaker Oats brands will enjoy the cost reduction, in which case the required cost reductions are over 80% and 90%, respectively.

6. Discussion

■ This article uses a structural model of demand and supply to simulate price equilibria and compute the social welfare changes resulting from various mergers. The

[21] With 95% confidence intervals of between 27.4 and 87.6 million, and 18.5 and 36.0, respectively.

approach is used to examine five mergers in the ready-to-eat cereal industry: two actual, one attempt to merge that was later withdrawn, and two hypothetical. Postmerger equilibrium outcomes are simulated under a variety of assumptions on the cost-reduction effects of the mergers. In addition, the model is used to generate welfare implications of the new equilibrium.

Since two of the mergers actually occurred, a natural question is how well the model predicts the outcome. I do not have detailed data, as used in estimation, for the postmerger period. Therefore, I cannot conduct formal tests of the predictions. However, some informal analysis can be performed. Figure 3 shows that the price of Shredded Wheat went down after the merger. There was a significant decline in the price in 1994, but one could claim this was due to the court proceedings that were still in progress and does not reflect the unconstrained profit-maximizing price. In 1995 the price of Shredded Wheat was roughly equal to the price in 1993. This is not statistically different from the prediction of the no-cost-saving model and is almost exactly equal to the point estimate assuming 5% cost savings. The price of Chex stayed around \$3.80 per pound at the end of 1996 and during 1997. However, during this period the average price of branded cereal dropped by roughly 8%. Once again, this is almost identical to the prediction of the 5% cost-reduction model.

The model is also able to predict profits generated by the mergers. In principle, the present discounted value of incremental profits could be compared to the price paid by the acquired firm. Post paid \$450 million for the Nabisco cereal line, which at the time of purchase generated roughly \$160 million in sales per year, compared to \$200 million two years earlier. At the standard, for this industry, 15–20% pretax profit-to-sales ratio,[22] this yields \$24–\$32 million a year, or \$30–\$40 million at the 1990 sales. These returns make this a reasonable investment. However, it is highly probable that Post expected to experience lower marginal costs after the merger. If the cost savings were of the order of magnitude of those considered in Table 7, such efficiency gains would contribute an additional \$10 million a year, making this a solid investment even before realizing any gains from new brand introductions and advertising. General Mills paid \$560 million for the Chex cereal and snack line, which generated sales of \$420 million, including \$80 million in Chex Mix sales. These sales are likely to yield pretax profits of \$60–\$80 million per year, suggesting that the price paid reflected General Mills' expectation of relatively small cost efficiencies.

There could be other dimensions of nonprice competition between cereal manufacturers, e.g., advertising and brand introduction. The analysis in this article does not take into account any postmerger changes in behavior in these dimensions. For example, merging firms might change the number of new brands, or the way in which new brands are introduced (Werden and Froeb, 1998; Cabral, 1999). Such changes could have a direct effect on consumer welfare and an indirect effect on long-run prices. The direct effect might increase (decrease) consumer welfare through more (less) variety. However, the long-run effect might be to create a barrier to entry (Schmalensee, 1978), thus supporting higher long-run prices. In order to determine if these effects exist, and which one dominates, we need a dynamic model of brand introduction.

Nonprice dimensions could be introduced by simulating the effects a merger would have on the policy functions determining these strategies. However, an empirical model of dynamic decisions, such as advertising and brand introduction, is beyond current

[22] As presented in Table 4, the average predicted cost-price margin is approximately 50%. After accounting for fixed costs and advertising, we get the 15–20% pretax profits-to-sales ratio (Nevo, forthcoming).

knowledge. The algorithm offered by Pakes and McGuire (1994)[23] is promising as a basis for future work.

Appendix A

■ This Appendix contains additional information on data construction and estimation.

□ **Data.** The data described in Section 4 were obtained from various sources. Quantity and price data were obtained from the Food Marketing Policy Center at the University of Connecticut. These data were collected by Information Resources, Inc. (IRI) using scanning devices in a national random sample of supermarkets located in various metropolitan areas and rural towns. Weekly data for UPC-coded products are drawn from a sample that represents the universe of supermarkets with annual sales of more than $2 million, accounting for 82% of grocery sales in the United States. In most cities the sample covers more than 20% of the relevant population. Due to the importance of the sample to its customers, IRI makes an effort to make the sample representative. This is confirmed by unpublished analysis conducted by the Bureau of Labor Statistics.

Market shares are defined by converting volume sales into number of servings sold,[24] and dividing by the total potential number of servings in a city in a quarter. This potential was assumed to be one serving per capita per day. The market share of the outside good was defined as the difference between one and the sum of inside goods market shares. A price variable was created by dividing the dollar sales by the number of servings sold, and deflated using a regional urban consumers CPI. The dollar sales reflect the price paid by consumers at the register, generating an average real per-serving transaction price.

Advertising data were taken from the Leading National Advertising database, which contains quarterly national advertising expenditures from ten media sources for each brand.[25] The advertising variable is defined as the total expense for the ten types of media. Product characteristics were collected in local supermarkets by examining cereal boxes. This implicitly assumes that the characteristics have not changed since 1988. Although this is not exactly true, it seems a reasonable first approximation. Each cereal was classified into "mushy" or not, depending on its sogginess in milk.[26]

Information on the distribution of demographics was obtained by sampling individuals from the March Current Population Survey for each year. I sampled forty draws for each city in each year. Individual income was obtained by dividing household income by the size of the household. The variable *Child* was defined as a dummy variable equal to one if age is less than sixteen. The national averages obtained here are representative of Census statistics.

Finally, instrumental variables were constructed using two additional data sources. An average of wages paid in the supermarket sector in each city was constructed from the NBER CPS Monthly Earning Extracts. Estimates of city density were taken from the Bureau of Labor Statistics, as were regional price indices.

Summary statistics for all variables are presented in a table available at http://emlab.berkeley.edu/-nevo.

□ **Estimation.** Let $Z = [z_1, \ldots, z_M]$ be a set of instruments such that

$$E[Z' \cdot \omega(\theta^*)] = 0, \tag{A1}$$

where ω, a function of the model parameters, is an error term defined below and θ^* denotes the true value of these parameters. The GMM estimate is

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\ \omega(\theta)' Z A^{-1} Z' \omega(\theta), \tag{A2}$$

where A is a consistent estimate of $E[Z'\omega\omega' Z]$. Following Berry (1994), I define the error term by solving for the mean utility levels, $\delta_{.t}$, common to all individuals, that solve the implicit system of equations

$$s_{.t}(x_{.t}, p_{.t}, \delta_{.t}; \theta_2) = S_{.t}, \tag{A3}$$

where $s_{.t}(\cdot)$ is the market share function defined by equation (2), $S_{.t}$ are the observed market shares, and θ_2

[23] See also Gowrisankaran (1995).

[24] I use the serving weight suggested by the manufacturer, which is assumed correct (or at least proportional to the "true" serving weight).

[25] The sources include magazines, Sunday magazines, newspapers, outdoor advertising, network television, spot television, syndicated television, cable networks, network radio, and national spot radio.

[26] I wish to thank Sandy Black for suggesting this variable and helping me classify the various brands.

is a parameter vector, which includes Π and Σ in the notation of Section 3. For the logit model the solution, $\delta_{jt}(x_{.t}, p_{.t}, S_{.t}; \theta_2)$, is equal to $\ln(S_{jt}) - \ln(S_{0t})$, while for the full model this inversion is done numerically. Once this inversion has been done, the error term is defined as

$$\omega_{jt} = \delta_{jt}(x, p_{.t}, S_{.t}; \theta_2) - (x_j\beta + \alpha p_{jt}). \tag{A4}$$

If we want to include brand, time, or city variables, they would also be included in the right-hand side.

In the logit model, with the appropriate choice of a weight matrix, this procedure simplifies to two-stage least-squares regression using $\ln(S_{jt}) - \ln(S_{0t})$ as the dependent variable. In the full random coefficients model, both the computation of the market shares and the inversion to get $\delta_{jt}(\cdot)$ have to be done numerically. The value of the estimate in equation (A2) is then computed using a nonlinear search. For details of the computation algorithm, including a MATLAB computer code, see Nevo (2000).

The empirical specification includes a brand dummy variable as one of the product characteristics. However, the coefficients on these variables are not allowed to vary by individual. This variable captures the effects of all brand characteristics, observed and unobserved, that are constant across markets, improves the fit of the model, and reduces the endogeneity problem (by controlling for some of the unobserved quality). To recover the mean taste for any observed characteristic that is fixed between markets, a minimum distance procedure is used (Chamberlain, 1982).

Let $d = (d_1, \ldots, d_J)'$ denote the $J \times 1$ vector of brand dummy coefficients, X be the $J \times K$ ($K < J$) matrix of product characteristics, and $\xi = (\xi_1, \ldots, \xi_J)'$ be the $J \times 1$ vector of unobserved product qualities. Then, from equation (1),

$$d = X\beta + \xi.$$

If we assume that $E[\xi | X] = 0$,[27] the estimates of β and ξ are

$$\hat{\beta} = (X'V_d^{-1}X)^{-1}X'V_d^{-1}\hat{d}, \qquad \hat{\xi} = \hat{d} - X\hat{\beta},$$

where $\hat{d}$ is the vector of coefficients estimated from the GMM procedure described above, and V_d is the variance-covariance matrix of these estimates. The coefficients on the brand dummies provide an "unrestricted" estimate of the mean utility. The minimum distance procedure projects these estimates onto a lower dimensional space, which is implied by a "restricted" model that sets ξ to zero. This provides a χ^2 test to evaluate these restrictions.

Appendix B

■ This Appendix presents tests of the identifying assumption. As was pointed out in Section 4, there are several reasons to doubt the independence assumption of demand shocks across cities required to justify the instrumental variables. For example, consider a national (or regional) demand shock, such as the discovery that fiber reduces the risk of cancer. This discovery will increase the unobserved valuation of all fiber-intensive brands in all cities, and the independence assumption will be violated. The results concentrate on well-established brands, and aggregate demand shocks are captured by time dummy variables. Nevertheless, based on theoretical arguments one cannot completely rule out the possibility of correlation in the demand shocks.

Determining the plausibility of the instruments is an empirical issue. I examine another set of instrumental variables, which proxies for the marginal costs directly, and compare the difference between the estimates implied by these different sets of instrumental variables. The marginal costs include production (materials, labor, and energy), packaging, and distribution costs. Direct production and packaging costs exhibit little variation and are too small a percentage of marginal costs to be correlated with prices. Also, except for small variations over time, a brand dummy variable, which is included as one of the regressors, proxies for these costs. The last component of marginal costs, distribution costs, includes the cost of transportation, shelf space, and labor. These are proxied by region dummy variables, which pick up transportation costs; city density, which is a proxy for the difference in the cost of space; and average city earning in the supermarket sector computed from the CPS Monthly Earning Files.

There are not enough additional instrumental variables to estimate the full model. Therefore, I examine a restricted version of the full model, the logit model. In addition to exploring the instrumental variables,

[27] This assumption justifies the use of observed characteristics as instrumental variables. Here, unlike previous work, this assumption is used only to recover the taste parameters and does not affect the estimates of price sensitivity.

TABLE B1 Results from Logit Demand

Variable	OLS (1)	IV (2)	(3)	(4)	(5)	(6)
Price	−8.57	−12.60	−12.65	−16.61	−16.97	−18.21
	(.179)	(.436)	(.467)	(.443)	(.483)	(.439)
Advertising	.034	.032	.032	.030	.030	.030
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Log median income	—	—	—	.99	1.00	1.01
				(.021)	(.022)	(.022)
Log of median age	—	—	—	−.02	.01	.04
				(.06)	(.06)	(.06)
Median household size	—	—	—	−.03	−.02	−.02
				(.03)	(.03)	(.03)
Measure of fit[a]	.76	99.1	98.7	59.0	51.3	54.8
		(30.1)	(16.9)	(30.1)	(16.9)	(42.6)
First stage						
R^2	—	94.5	94.4	94.5	94.5	94.7
F-statistic	—	5,179	6,740	5,046	6,483	4,959
Instruments						
Average regional prices	—	X	—	X	—	X
Cost proxies	—	—	X	—	X	X
Own price elasticity						
Mean	−1.71	−2.51	−2.51	−3.31	−3.38	−3.62
Standard	.51	.75	.75	.99	1.01	1.09
Median	−1.60	−2.36	−2.36	−3.11	−3.18	−3.41
% of inelastic demands	4.4%	0	0	0	0	0
(± 2 standard errors)	(4.1–4.9%)					

Number of observations is 21,600. Dependant variable is $\ln(S_{jt}) - \ln(S_{0t})$. All regressions include time and brand dummy variables: robust standard errors are given in parentheses.
[a] Adjusted R^2 for the OLS regression, and a test of overidentification for the instrumental-variables regressions with the .95 critical values in parentheses.

this model is interesting due to the emphasis it has received in the merger literature (Werden and Froeb, 1994).

Table B1 presents results obtained by regressing the difference of the log of each brand's observed market share and the log of the share of the outside good, $\ln(S_{jt}) - \ln(S_{0t})$, on price, advertising expenditures, brand, and time dummy variables. Column 1 displays the results of ordinary least squares. The coefficient on price and the implied own-price elasticities are relatively low. The logit demand structure does not impose a constant elasticity, and therefore the estimates imply a different elasticity for each brand-city-quarter combination. Some statistics of the own-price elasticity distribution are shown at the bottom of each column. The low elasticities and the high number of inelastic demands are not uncommon and are due to the endogeneity of prices.

Two sets of instrumental variables were explored to deal with this problem. Columns 2 and 4 present two-stage least-squares estimates using the average regional prices, described in Section 4, as instrumental variables. Columns 3 and 5 use the proxies for marginal costs described above as instrumental variables in the same regression. Finally, column 6 uses both sets of instrumental variables. Columns 4–6 include controls for market demographics.

Three conclusions should be drawn from the results in Table B1. First, once instrumental variables are used, the coefficient on price and the implied own-price elasticity increase in absolute value. This is predicted by theory and holds in a wide variety of studies. Second, even though there are reasons to doubt the validity of the first set of instruments, they seem to generate results almost identical to those produced by using the cost proxies. The similarity between the coefficients does not promise the two sets of instrumental variables will produce identical coefficients in different models or that these are valid instrumental variables. However, the finding does provide some support for the validity of the instrumental variables used. Finally, the results demonstrate the importance of controlling for demographics and heterogeneity, which the full model does.

The limitations of the logit model for merger analysis are well known (McFadden, 1981; Berry, Levinsohn, and Pakes, 1995). Nevertheless, I present some of the implications of the results. The implied marginal costs are presented in Table 4. Another table, available at http://emlab.berkeley.edu/~nevo, presents the implied estimates of own- and cross-price elasticities. There are two disturbing patterns in this table, both predicted by theory and both due to the logit functional form. First, the own-price elasticities, presented in the second column, are almost exactly linear in price. This is due to the lack of heterogeneity in the price coefficient and the fact that price enters in a linear form.[28] Second, the cross-price elasticities are forced to be equal, and I need only present one number for each brand. This is probably the main limitation of using the logit model for merger analysis.

References

BAKER, J.B. "Contemporary Empirical Merger Analysis." *George Mason Law Review*, Vol. 5 (1997), pp. 347–361.

——— AND BRESNAHAN, T.F. "The Gains from Merger or Collusion in Product-Differentiated Industries." *Journal of Industrial Economics*, Vol. 33 (1985), pp. 427–444.

BERRY, S.T. "Estimating Discrete-Choice Models of Product Differentiation." *RAND Journal of Economics*, Vol. 25 (1994), pp. 242–262.

——— AND PAKES, A. "Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis." *American Economic Review*, Vol. 83 (1993), pp. 247–252.

———, LEVINSOHN, J., AND PAKES, A. "Automobile Prices in Market Equilibrium." *Econometrica*, Vol. 63 (1995), pp. 841–890.

BRESNAHAN, T.F. "Empirical Studies of Industries with Market Power." In R. Schmalensee and R.D. Willig, eds., *Handbook of Industrial Organization*. Amsterdam: North-Holland, 1989.

———, STERN, S., AND TRAJTENBERG, M. "Market Segmentation and the Sources of Rents from Innovation: Personal Computers in the Late 1980s." *RAND Journal of Economics*, Vol. 28 (1997), pp. S17–S44.

CABRAL, L. "Horizontal Mergers with Free Entry: Why Cost Efficiencies May Be a Weak Defense and Asset Sales a Poor Remedy." Mimeo, London Business School, 1999.

CARDELL, N.S. "Extensions of the Multinomial Logit: The Hedonic Demand Model, The Non-Independent Logit Model, and the Ranked Logit Model." Ph.D. dissertation, Department of Economics, Harvard University, 1989.

CHAMBERLAIN, G. "Multi Variate Regression Models for Panel Data." *Journal of Econometrics*, Vol. 18 (1982), pp. 5–46.

DAS, S., OLLEY, S., AND PAKES, A. "Evolution of Brand Qualities of Consumer Electronics in the U.S." Mimeo, Department of Economics, Yale University, 1994.

DUBIN, J.A. AND MCFADDEN, D.L. "An Econometric Analysis of Residential Electric Appliance Holding and Consumption." *Econometrica*, Vol. 52 (1984), pp. 345–362.

ELLISON, S.F., COCKBURN, I., GRILICHES, Z., AND HAUSMAN, J. "Characteristics of Demand for Pharmaceutical Products: An Examination of Four Cephalosporins." *RAND Journal of Economics*, Vol. 28 (1997), pp. 426–446.

GOWRISANKARAN, G. "A Dynamic Analysis of Mergers." Ph.D. dissertation, Department of Economics, Yale University, 1995.

HAUSMAN, J.A. "Valuation of New Goods Under Perfect and Imperfect Competition." In T.F. Bresnahan and R. Gordon, eds., *The Economics of New Goods*. Chicago: National Bureau of Economic Research, 1996.

——— AND LEONARD, G. "Economic Analysis of Mergers in Differentiated Products Industries: Mergers Using Real World Data." *George Mason Law Review*, Vol. 5 (1997), pp. 321–346.

———, ———, AND ZONA, J.D. "Competitive Analysis with Differentiated Products." *Annales D'Economie et de Statistique*, Vol. 34 (1994), pp. 159–180.

[28] If price entered in a log form, these elasticities would all be roughly equal. Beyond the discussion of which is the "correct" functional form, this is disturbing because arbitrary assumptions on functional forms will determine a key result.

HENDEL, I. "Estimating Multiple Discrete-Choice Models: An Application to Computerization Returns." *Review of Economic Studies,* Vol. 66 (1999), pp. 423–446.

MCFADDEN, D. "Conditional Logit Analysis of Qualitative Choice Behavior." In P. Zarembka, ed., *Frontiers of Econometrics.* New York: Academic Press, 1973.

———. "Modeling the Choice of Residential Location." In A. Karlqvist, L. Lundqvist, F. Snickars, and J. Weibull, eds., *Spatial Interaction Theory and Planning Models.* New York: North-Holland, 1978.

———. "Econometric Models of Probabilistic Choice." In C.F. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data.* Cambridge, Mass.: MIT Press, 1981.

———. "Computing Willingness-to-Pay in Random Utility Models." Mimeo, Department of Economics, University of California, Berkeley, 1995.

NEVO, A. "Demand for Ready-to-Eat Cereal and Its Implications for Price Competition, Merger Analysis and Valuation of New Brands." Ph.D. dissertation, Department of Economics, Harvard University, 1997.

———. "A Practitioner's Guide to Random Coefficients Logit Models of Demand." *Journal of Economics and Management Strategy,* Vol. 9 (2000).

———. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica* (forthcoming).

——— AND WOLFRAM, C. "Prices and Coupons for Breakfast Cereals." Working Paper no. 6932, National Bureau of Economic Research, 1999.

PAKES, A. AND MCGUIRE, P. "Computation of Markov-Perfect Equilibria: Numerical Implications of a Dynamic Differentiated Product Model." *RAND Journal of Economics,* Vol. 25 (1994), pp. 555–589.

SCHERER, F.M. "The Breakfast Cereal Industry." In W. Adams, ed., *The Structure of American Industry.* New York: Macmillian, 1982.

SCHMALENSEE, R. "Entry Deterrence in the Ready-to-Eat Breakfast Cereal Industry." *Bell Journal of Economics,* Vol. 9 (1978), pp. 305–327.

SMALL, K.A. AND ROSEN, H.S. "Applied Welfare Economics with Discrete Choice Models." *Econometrica,* Vol. 49 (1981), pp. 105–130.

VELLTURO, C.A. "Creating an Effective Diversion: Evaluating Mergers with Differentiated Products." *Antitrust,* Vol. 11 (1997), pp. 16–20.

WERDEN, G.J. "The History of Antitrust Market Delineation." *Marquette Law Review,* Vol. 76 (1992), pp. 123–215.

———. "Market Delineation Under the Merger Guidelines: A Tenth Anniversary Retrospective." *Antitrust Bulletin,* Vol. 38 (1993), pp. 517–555.

———. "Simulating Unilateral Competitive Effects from Differentiated Product Mergers." *Antitrust,* Vol. 11 (1997), pp. 27–31.

——— AND FROEB, L.M. "The Effects of Mergers in Differentiated Products Industries: Logit Demand and Merger Policy." *Journal of Law, Economics and Organization,* Vol. 10 (1994), pp. 407–426.

——— AND ———. "Simulation as an Alternative to Structural Merger Policy in Differentiated Products Industries." In M.B. Coate and A.N. Kleit, eds., *The Economics of the Antitrust Process.* Boston: Kluwer, 1996.

——— AND ———. "The Entry-Inducing Effects of Horizontal Mergers: An Exploratory Analysis." *Journal of Industrial Economics,* Vol. 46 (1998), pp. 525–543.

——— AND ROZANSKI, G.A. "The Application of Section 7 to Differentiated Products Industries: The Market Delineation Dilemma." *Antitrust,* Vol. 8 (1994), pp. 40–43.

WILLIG, R.D. "Merger Analysis, Industrial Organization Theory, and the Merger Guidelines." *Brookings Papers on Economic Activity, Microeconomics,* (1991), pp. 281–332.

LINKED CITATIONS

You have printed the following article:

Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry
Aviv Nevo
The RAND Journal of Economics, Vol. 31, No. 3. (Autumn, 2000), pp. 395-421.
Stable URL:
http://links.jstor.org/sici?sici=0741-6261%28200023%2931%3A3%3C395%3AMWDPTC%3E2.0.CO%3B2-0

This article references the following linked citations. If you are trying to access articles from an off-campus location, you may be required to first logon via your library web site to access JSTOR. Please visit your library's website or contact a librarian to learn about options for remote access to JSTOR.

[Footnotes]

[2] **The Gains from Merger or Collusion in Product-Differentiated Industries**
Jonathan B. Baker; Timothy F. Bresnahan
The Journal of Industrial Economics, Vol. 33, No. 4, A Symposium on Oligopoly, Competition and Welfare. (Jun., 1985), pp. 427-444.
Stable URL:
http://links.jstor.org/sici?sici=0022-1821%28198506%2933%3A4%3C427%3ATGFMOC%3E2.0.CO%3B2-G

[2] **Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis**
Steven Berry; Ariel Pakes
The American Economic Review, Vol. 83, No. 2, Papers and Proceedings of the Hundred and Fifth Annual Meeting of the American Economic Association. (May, 1993), pp. 247-252.
Stable URL:
http://links.jstor.org/sici?sici=0002-8282%28199305%2983%3A2%3C247%3ASAALOR%3E2.0.CO%3B2-V

[7] **The Gains from Merger or Collusion in Product-Differentiated Industries**
Jonathan B. Baker; Timothy F. Bresnahan
The Journal of Industrial Economics, Vol. 33, No. 4, A Symposium on Oligopoly, Competition and Welfare. (Jun., 1985), pp. 427-444.
Stable URL:
http://links.jstor.org/sici?sici=0022-1821%28198506%2933%3A4%3C427%3ATGFMOC%3E2.0.CO%3B2-G

NOTE: *The reference numbering from the original has been maintained in this citation list.*

[7] **Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis**

Steven Berry; Ariel Pakes

The American Economic Review, Vol. 83, No. 2, Papers and Proceedings of the Hundred and Fifth Annual Meeting of the American Economic Association. (May, 1993), pp. 247-252.

Stable URL:

http://links.jstor.org/sici?sici=0002-8282%28199305%2983%3A2%3C247%3ASAALOR%3E2.0.CO%3B2-V

[12] **Estimating Discrete-Choice Models of Product Differentiation**

Steven T. Berry

The RAND Journal of Economics, Vol. 25, No. 2. (Summer, 1994), pp. 242-262.

Stable URL:

http://links.jstor.org/sici?sici=0741-6261%28199422%2925%3A2%3C242%3AEDMOPD%3E2.0.CO%3B2-Z

References

The Gains from Merger or Collusion in Product-Differentiated Industries

Jonathan B. Baker; Timothy F. Bresnahan

The Journal of Industrial Economics, Vol. 33, No. 4, A Symposium on Oligopoly, Competition and Welfare. (Jun., 1985), pp. 427-444.

Stable URL:

http://links.jstor.org/sici?sici=0022-1821%28198506%2933%3A4%3C427%3ATGFMOC%3E2.0.CO%3B2-G

Estimating Discrete-Choice Models of Product Differentiation

Steven T. Berry

The RAND Journal of Economics, Vol. 25, No. 2. (Summer, 1994), pp. 242-262.

Stable URL:

http://links.jstor.org/sici?sici=0741-6261%28199422%2925%3A2%3C242%3AEDMOPD%3E2.0.CO%3B2-Z

Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis

Steven Berry; Ariel Pakes

The American Economic Review, Vol. 83, No. 2, Papers and Proceedings of the Hundred and Fifth Annual Meeting of the American Economic Association. (May, 1993), pp. 247-252.

Stable URL:

http://links.jstor.org/sici?sici=0002-8282%28199305%2983%3A2%3C247%3ASAALOR%3E2.0.CO%3B2-V

LINKED CITATIONS

Automobile Prices in Market Equilibrium
Steven Berry; James Levinsohn; Ariel Pakes
Econometrica, Vol. 63, No. 4. (Jul., 1995), pp. 841-890.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28199507%2963%3A4%3C841%3AAPIME%3E2.0.CO%3B2-U

Market Segmentation and the Sources of Rents from Innovation: Personal Computers in the Late 1980s
Timothy F. Bresnahan; Scott Stern; Manuel Trajtenberg
The RAND Journal of Economics, Vol. 28, No. 0, Special Issue in Honor of Richard E. Quandt. (1997), pp. S17-S44.
Stable URL:
http://links.jstor.org/sici?sici=0741-6261%281997%2928%3CS17%3AMSATSO%3E2.0.CO%3B2-R

An Econometric Analysis of Residential Electric Appliance Holdings and Consumption
Jeffrey A. Dubin; Daniel L. McFadden
Econometrica, Vol. 52, No. 2. (Mar., 1984), pp. 345-362.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198403%2952%3A2%3C345%3AAEAORE%3E2.0.CO%3B2-Y

Characteristics of Demand for Pharmaceutical Products: An Examination of Four Cephalosporins
Sara Fisher Ellison; Iain Cockburn; Zvi Griliches; Jerry Hausman
The RAND Journal of Economics, Vol. 28, No. 3. (Autumn, 1997), pp. 426-446.
Stable URL:
http://links.jstor.org/sici?sici=0741-6261%28199723%2928%3A3%3C426%3ACODFPP%3E2.0.CO%3B2-P

Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns
Igal Hendel
The Review of Economic Studies, Vol. 66, No. 2. (Apr., 1999), pp. 423-446.
Stable URL:
http://links.jstor.org/sici?sici=0034-6527%28199904%2966%3A2%3C423%3AEMCMAA%3E2.0.CO%3B2-Z

NOTE: *The reference numbering from the original has been maintained in this citation list.*

LINKED CITATIONS

Computing Markov-Perfect Nash Equilibria: Numerical Implications of a Dynamic Differentiated Product Model

Ariel Pakes; Paul McGuire

The RAND Journal of Economics, Vol. 25, No. 4. (Winter, 1994), pp. 555-589.

Stable URL:

http://links.jstor.org/sici?sici=0741-6261%28199424%2925%3A4%3C555%3ACMNENI%3E2.0.CO%3B2-9

Applied Welfare Economics with Discrete Choice Models

Kenneth A. Small; Harvey S. Rosen

Econometrica, Vol. 49, No. 1. (Jan., 1981), pp. 105-130.

Stable URL:

http://links.jstor.org/sici?sici=0012-9682%28198101%2949%3A1%3C105%3AAWEWDC%3E2.0.CO%3B2-Z

NOTE: *The reference numbering from the original has been maintained in this citation list.*