Demand System Estimation and its Application To Horizontal Merger Analysis[†*]

Daniel Hosken

Daniel O'Brien

David Scheffman

Michael Vita

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Abstract

The past decade has witnessed remarkable developments in the quantitative analysis of horizontal mergers. Increases in computing power and the quantity and quality of data available have substantially reduced the costs of estimating demand systems using econometric methods. Good estimates of retail demand elasticities can make an important contribution to assessing the potential effects of a manufacturer merger on consumer prices. While estimates of demand relationships can make substantial contributions to merger analysis, it is much like every other area of empirical economics, in that practitioners invariably are forced to confront and resolve a series of difficult econometric and conceptual issues. The purpose of this paper is to identify a number of these issues that we believe researchers and practitioners should address, as a general matter, and in specific applications in which these issues are pertinent, with the ultimate goal of improving the quality of antitrust analysis.

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I. INTRODUCTION

The past decade has witnessed remarkable developments in the quantitative analysis of horizontal mergers. Several factors account for these changes. The quantity and quality of data available to estimate the degree of substitutability among competing products has increased dramatically. This increase has been accompanied by a substantial decrease in the price of computing power required to analyze the data. A third factor is an increased focus on the possibility of competitive harm from “unilateral” market conduct, particularly in mergers involving differentiated products. However, understanding how consumers substitute among competing products also can contribute substantially to the analysis of possible competitive harm from “coordinated” market behavior.

How consumers substitute across products as relative prices change is clearly relevant to understanding the potential price effects of mergers.[1] This information, contained in the own- and cross-price elasticities of demand at retail,[2] is most frequently used as means for predicting the “unilateral” incentives to increase prices post-merger. In the context of differentiated consumer goods, the term “unilateral effects” refers to the fact that a merger of competitors creates an incentive to increase price (*ceteris paribus*) to the extent that there are significant subs

Until quite recently, economists had to rely on relatively simple quantitative analyses (surveys, analysis of shift in share, *etc*.) and qualitative information (for example, an internal company document stating that products X, Y, and Z all compete with each other) – that did not permit quantification of the degree of substitutability among the merging firms' products. While these sources of information are useful and continue to play an important role in merger analysis, a well-executed econometric analysis of demand may enable an economist to infer not only that a set of goods are substitutes, but also to infer *what volume of sales* will switch from product X to product Y given (say) a specific price increase for product X.

The value of information on demand elasticities is not limited to situations where attention is focused primarily on unilateral pricing incentives. Evidence bearing on the degree of substitutability among potentially competing products is also important in determining the incentive and ability to engage in coordinated post-merger pricing.

In appraising the value of elasticity information gleaned from an econometric analysis of scanner data, is noteworthy that others, such as marketing professionals, also undertake similar analyses. For example, manufacturers of consumer products estimate systems of demand equations to help them determine optimal prices for their products. Clearly, scanner data, drawn from consumers' actual purchases, provides a wealth of information that can be used to describe and analyze consumer demand..

While the quantitative estimation of demand relationships can make substantial contributions to merger analysis, it is much like every other area of empirical economics, in that practitioners invariably are forced to confront and resolve a series of difficult econometric and conceptual issues. The purpose of this paper is to identify a number of econometric and conceptual issues that we believe researchers and practitioners should address in order to make the quantitative estimation of demand relationships using scanner data more applicable to merger review.

Briefly, we raise the following issues in this paper:

These are difficult questions, and we do not attempt to provide definitive answers to them. Our purpose instead is to provoke further discussion and research into these issues, with the ultimate goal of improving the quality of antitrust analysis.

II. DATA ISSUES

A. Scanner Data Features

The two leading providers of scanner data are A.C. Nielsen (Nielsen) and Information Resources Incorporated (IRI). Both firms provide a variety of retail information in a number of channels of distribution (supermarkets, drug stores, mass-merchandisers, and convenience stores) for various geographic regions throughout the U.S. The bases of these data sold by Nielsen and IRI are a sample of stores from which the data companies acquire all point-of-sale (POS) scanner data. The scanner data provides data on total revenue and total units sold by UPC code.[4] In addition, IRI and Nielsen collect a number of measures of price and of various measures of promotion for each retail outlet they sample, *e.g.*, a specific chain and store location, and a measure of distribution penetration.[5]

simply mentioned in the circular. Second, IRI and Nielsen record what proportion of stores have in-store promotional displays for items, e.g., an end of aisle display or some type of free-standing display. Finally, the firms record whether or not a coupon was released in a geographic area, typically as a “free-standing-insert” of the type found in the Saturday or Sunday edition of a newspaper. Including these measures of promotion can significantly enhance the accuracy of a demand study. However, if (as is typically the case) the data is aggregated across retailers, the aggregation to some extent “masks” the interactive effect between price promotions and other forms of promotions. For example, knowing that 50% of the retailers (by some measure of total sales) had an end aisle display does not allow us to match the price those stores set, since the measure of price is an average across the “market.”

Because many antitrust practitioners have a vague notion of what exactly scanner data is, we believe it is beneficial to explicitly describe the data used by the FTC in a recent court case. In *FTC v. Swedish Match*, both the Commission and respondents presented estimates of the own-price elasticity for loose-leaf chewing tobacco based on monthly data from all retail channels (supermarkets, drug stores, convenience stores, and mass-merchandisers) and aggregated across regions within a state. The data used by the FTC and Swedish Match in the studies presented to the Court was aggregated to the category level; that is, all UPCs of each brand (e.g, Red Man, Levi-Garret, or Beechnut Chewing Tobacco) were aggregated into a single number for loose leaf chewing tobacco. The data was also aggregated over: the time unit (from weekly to monthly), geography (all retailers within a state), retail channels (supermarkets, drug stores, mass merchandisers, convenience stores), retailers, brands, and UPC’s within the brand (package sizes). An example of an individual data point would be total dollar and unit sales of (all brands of) loose leaf chewing tobacco sold in Illinois in all measured retail channels for March, 1999. Below we discuss the potential problems associated with the various types of data aggregation that are required to conduct an econometric analysis with scanner data.

B. General Aggregation Issues

One of the most significant issues in using scanner data to estimate demand estimates is the nature and extent of data 04 Te total dollar and

1. Channel Aggregation

Most consumer products are sold in a number of different channels, however, it is often the case that some channels of distribution are more important for a given product than others. For example, many food products are sold almost exclusively through supermarkets, e.g., canned soup, salad dressing, and cake mix. In these cases, simply using data from the supermarket channel should be sufficient to describe the demand system for the products. Other product categories have large sales of products through multiple channels, e.g., soft drinks and snack food are sold in significant quantities through convenience stores, grocery stores and mass-merchandisers.

When consumers purchase the same consumer products through different channels, aggregation of sales and unit data across channels could lead to different elasticity estimates than if the elasticities were estimated separately by channel for at least two reasons. First, consumers choose to shop in different channels for different reasons. For example, consumers shopping at a convenience store likely have less elastic demand for products than those shopping at a supermarket. One would expect that consumers' beer purchases through convenience stores would be less sensitive to price than purchases through grocery stores. The same pattern likely holds when comparing products carried by one channel more as a convenience (such as motor oil at a supermarket) to retailers that specialize in selling those products (such as motor oil through a mass-merchandiser).

Second, the mix of package sizes of a given product/brand (e.g., *Pepsi Cola*) sold through different channels also varies significantly. For example, the share of single serve packages of cola (20 ounce bottles or 12 ounce cans) sold through convenience stores is much larger than that sold through supermarkets. If sales and revenue are calculated at the brand level (Pepsi) as opposed to the UPC level (20 ounce bottle of Pepsi, 2 liter bottle of Pepsi, 12 pack of Pepsi), then measures of revenue and *manufacturer* level, the frequency of scanner data presents other problems. Unlike retailers, manufacturers do not change their wholesale prices on a weekly basis.[7]

Time aggregation also relates to another problem that we will discuss further below -- purchasing for inventory. Using weekly or even monthly data may overestimate elasticities because consumers often buy large quantities of items which are on sale and take them into household inventories; that is, the elasticities being measured are really short run purchasing elasticities not the consumption elasticities which are relevant for antitrust analysis. Economics and marketing researchers both find that inventory effects can be important.[8] Because the goal of antitrust analysis is to measure the effects on consumer demand of permanent changes in price, it is important to measure elasticities that measure changes in consumer consumption due to changes in price. If inventory effects are important (this is likely to be the case if the predominate source of price variation are the sales which generate inventory effects), the estimated elasticities will likely be too large and should only serve as an upper bound for the demand elasticities for the purposes of antitrust analysis.

Empirically, we have found that elasticity estimated using weekly data are often larger than those estimated using monthly data.

3. Aggregation Across Product Sizes and Varieties

Many types of consumer products are sold in different package sizes, with the price per unit of weight or volume generally declining with package size. Further, it is sometimes the case that different package sizes are sold more through some channels of distribution than others. For example, maJ 0icice chasingnrib F 0.0004 Tc -0.0014 T0418.28 0Td [(diffnd fu(o)1(rn sal firms conduct sophisticated studies trying to determine how much substitution will take place between different package sizes of their own brands. In terms of estimating demand systems, we have observed that different aggregation rules (e.g., average price per pound, the creation of a price index, or estimating elasticities separately by package size) can lead to very different estimated demand elasticities. The fixes to this problem are not obvious or easy to undertake.[9]

C. Price Specification and Aggregation

The scanner data that is typically used in estimating demand curves is aggregated over some geographic area, e.g., a census region, state, or metro area, and across retailers, by channel, in that area. Obviously, if independent pricing decisions are made by stores within the geographic areas the price and quantity observed in the data (typically price defined as average revenue, and units defined as the sum of all units in the area) will not correspond to the prices charged (quantities sold) by any individual firm. There are two distinct types of problems that result from aggregation across retailers. The first comes from the observation that the aggregate price, as measured by average revenue, and aggregate output will not correspond to a point on the aggregate demand curve because average revenue is a non-linear function of each retailer's average revenue. The second set of problems are the result of un-modeled phenomena (e.g., sales, promotion, and other forms of retail competition) that cause consumers to not face the aggregate price as measured by average revenue. As discussed in more detail below, the second set of problems leads to more difficult questions on how to appropriately use price and quantity data to correctly estimate elasticities which manufacturers are likely to face.

A simple example can demonstrate how measuring price as average revenue can lead to biased elasticity estimates when demand curves are linear demand. Assume that there are three retailers operating in a geographic area, and, for simplicity, assume that the firms do not compete with one another because they are in separate geographic markets. The price and quantity data that the researcher observes is aggregated from the three firms. To be explicit assume that:

Firm 1's demand curve is: $Q = 1000 - 5*P$
Firm 2's demand curve is: $Q = 1000 - 8*P$
Firm 3's demand curve is: $Q = 1000 - 10*P$.

The aggregate demand firm for the region will be:

$Q = 3000 - 23*P$.

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9 In principal, one could attempt to formally incorporate the non-linear budget set into the econometric model, e.g., Reiss and White (2001). However, in the time required to estimate a demand system in a merger investigation this approach is not currently feasible. Instead, the approach BE has taken is to check the robustness of our results to different measures of price.

When we estimate a demand curve, we estimate a relationship like

$Q = \boldsymbol{A} - \boldsymbol{B} * P$,

where A and B are parameters to be estimated, and we use a single measure of price (aggregated in some manner; *e.g.*, average revenue)

If each firm charges the same price at every point in time, we can correctly estimate the demand curve using average revenue as the measure of price. However if the three firms charge different prices at the same point in time, then the estimated aggregate demand curve will not correspond to the true aggregate demand curve.

To illustrate the misspecification we conduct a simple simulation with 1500 price (and corresponding quantity) draws for each firm where firms 1, 2, and 3 set prices independently (but where prices were drawn from the same distribution), and find that the least squares estimate of the demand curve using the average unit price as the measure of price is: $Q = 2687 - 19.3*P$, which represents a significant underestimate of the true slope of the demand curve (see Figure 1 which presents a plot of the average price and total quantity data).[10]

[10] In the simulation we model each retailer as randomly drawing prices from a uniform distribution with prices between 0 and 100.

point in time. For example, it is well known that advertisements in circulars and in-store promotional activity (e.g., end of aisle displays) have large effects on unit sales.[14]

If a given chain charges approximately the same prices and offers similar promotions within a metro area, chain-specific data should accurately reflect the price and non-price attributes facing consumers in a given week. IRI and Nielsen do maintain these data; however, they have rarely been used in antitrust investigations.

While retailer-specific data reduce the problem of measurement error, the demand parameters estimated from retailer-specific data do not necessarily correspond to the parameters of interest to antitrust economists. The goal of the demand study is to determine the demand elasticities facing the manufacturer, commodities being analyzed by the particular choice of functional form) – or to put it more simply, they want to allow the data to tell them whether two goods are substitutes, and if so, whether they are close or distant substitutes).

The problem researchers face is that "flexibili

B. Choosing Functional Forms

Here we will focus principally on the functional forms that have experienced widespread use in merger simulations; readers seeking a more general discussion are referred to Deaton and Muellbauer (1980).

In estimating demand at retail, the researcher must choose the mathematical formula (functional form) that expresses the demand relationship. The statistical estimation, itself, does not "choose" the functional form. In theory, there is a "true" functional form that generates the purchase data, and of course it is important that the functional form chosen for estimation approximates the "true" functional form. As a matter of practice, assessing the validity of the functional form chosen for estimation is done through various statistical tests and testing alternative functional forms.

In the typical antitrust setting in which demand estimation and merger simulation occurs, the researcher will have data for a number of different cities *(e.g.,* 30 of the largest cities in the U.S.). For each product (or brand) analyzed, the dataset will consist of the number of units sold in some particular time period (*e.g.,* a week), a measure of the price that prevailed during that period,[17] and also measures of promotional activity for each product. Using standard econometric techniques,[18] the researcher will estimate a statistical relationship between the quantity of the good purchased and the price and promotional activities and other determinants of demand (such as the size of the market).

Choice of functional form can have major implications for the magnitude of predicted prices. Crooke *et al.* (1999) show that different functional forms can produce substantially differing predictions about post-merger equilibria. For example, if the researcher assumes that the demand functions exhibit constant elasticities, the predicted post-merger price increases will be much larger than if linear or logit demands are assumed.

One possible functional form is the linear demand system. One major advantage to the linear demand system is that it makes computation of the merger's competitive effects relatively easy (see Werden (1996) for details). There are numerous drawbacks to the linear demand system. First, there is no guarantee that the estimated parameters will have the "right" sign. If the different brands are substitutes, then the cross-price terms should be positive, in order to yield a positive cross-elasticity. However, it is frequently the case in applied work that the estimated cross-price coefficients will be negative, which calls into question the validity of the empirical exercise.

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[17] As discussed above, the measure of "price" typically used is average revenue (= (p*q)/ q), which often will not give an accurate measure of the prices actually faced by consumers during that week. For purposes of the present discussion, however, we will ignore this issue.

[18] We defer to Section III the economic and econometric issues associated with egc -0.dogenef

A second, more subtle problem is identified by Crooke *et al.* (1999), who found that simulations conducted with linear demand systems sometimes can yield *negative* predicted quantities.

An alternative to linear demand systems is the *log-linear* (*i.e.,* constant elasticity) demand function. This system is estimated by regressing the natural logarithms of the quantity variables on the natural logarithms of the price and demand-shifting variables. The appeal of the constant elasticity system is that the regression coefficients are the elasticities – no further computations are required. There are several disadvantages to this functional form. First, the "adding-up" restriction of demand theory (i.e., the requirement that expenditure shares sum to unity) cannot be satisfied by the constant elasticity demand system (Deaton and Muellbauer, 1980, p. 17). Second, many researchers prefer to allow demand elasticities to vary as prices and quantities vary (*e.g.,* as in the linear, logit, and AIDS demand systems, where demand becomes more elastic as one moves up the demand curve). If the true demand system is not constant elasticity, yet the researcher assumes otherwise for the purpose of merger simulation, the resulting predicted price increases can substantially overstate the likely price effects (Crooke *et al.* (1999)). A third disadvantage is that, depending on the values taken on by the elasticities, merger simulations may lead to a situation in which post-merger equilibrium does not always exist (Crooke *et al.* 1999). Last, the log-linear system, like the linear system, cannot guarantee that the parameters have the "right" signs.

The disadvantages of the linear and log-linear systems are sufficiently large that many researchers now use alternative functional forms in merger analysis.[19] One popular choice is the *Almost Ideal Demand System* (popularly termed the "AIDS" model), first proposed by Deaton and Muellbauer (1980), and advocated by Hausman *et al.* (1994) as a basis for empirical merger analysis. In the AIDS model, expenditure shares of each product are regressed on the logarithms of the prices of the different goods and the log of total expenditure (deflated by a price index). The principal disadvantages are that, like other functional forms (*e.g.,* linear), it requires the estimation of a large number of parameters, and it does not guarantee (at least without further restrictions) that cross-elasticities have the "right" signs. Additionally, although AIDS allows elasticities to adjust as equilibrium prices and quantities vary, it restricts somewhat the way these adjustments take place; consequently, the predictions of models estimated using the AIDS specification do not vary greatly from those estimated under an assumption of constant elasticities (Crooke *et al*. (1999, Table III)).

The burden of estimating a large number of that the consumer chooses the brand of cereal yielding the highest utility (he also has the alternative of choosing "none of the above," which is referred to as the "outside good."). With aggregate share data, the parameters of a simple logit model can be estimated as follows:

$$\log(S_j/S_O) = \beta * x_j + \alpha * p_j + \gamma * \log(S_{j|g}) + \varepsilon_j$$

Here, S_j is the market share of product "j"; S_O is the share of the "outside good;" x_j are characteristics of good "j"; p_j

Pakes (1995); Nevo (2000)) have proposed a random coefficients logit model that assumes that products can be viewed as bundles of characteristics (*e.g.*, automobiles might be characterized by horsepower, passenger space, and air conditioning). Accordingly, their empirical model is specified in terms of the demand for these characteristics, which are far fewer in number than the number of products (or brands) that compete in the market at any given time. The data required to estimate the random coefficients logit model may not always be particularly demanding – in some cases, they can be estimated with market-level price and quantity data, data on product characteristics, and information on the distribution of consumer attributes (*e.g.*, income, education) – but the estimation procedure itself is complex and time-consuming. The full details of the BLP approach are too complex to be presented in detail here. Nevo (2000) provides an excellent summary.

IV. Estimation Issues

A. Endogeneity

For statistical analysis of sample data to produce "reliable" results -- that is, results that accurately convey information about the underlying population -- certain conditions must hold. The data we use in the estimation is the product of both demand-side and supply-

(2001, p. 153), “[i]t is a basic principle of sound econometrics that *every serious estimate deserves a reliable assessment of precision,*

of reductions from the list price and/or net payments from the manufacturer in various each widget as *w*

These are strong assumptions that might be plausible in some applications, but clearly not in all settings.

Outside of these special cases, the relationship between the elasticities at different levels in the production chain is not one-to-one. In general, the relationship depends on the shape of demand curves and the nature of competition. Given assumptions about these factors, it is possible to calculate the relationship. For example, in the special case of linear demand, a retail marginal cost of *w*, and monopoly at the manufacturer and retail levels, it can be shown that $w/p = 2/3$ and that the pass-through rate is ½. In this case the derived demand elasticity is one-third the retail elasticity. Other common demand curves (e.g., semi-log, AIDS, and constant elasticity) yield pass-through rates that exceed ½. The derived demand elasticity is closer to the retail elasticity in these cases than it is under linear demand, other factors equal.

The relationship becomes considerably more complicated for multi-product retailers that compete with one another. We discuss three complications here that relate to institutions that are prevalent in the retailing environment.

One complication is the "one-stop shopping" nature of retail outlets, which generates demand-side complementarities among products on the shelf that are unrelated to consumers Tw -2 shewnsumers -0.0eels si88d monopol03 le, in thpeciaa lowualpricedf, ibe pllkTc -0.0016 T

A simple example illustrates this point. Imagine a market in which four manufacturers---A, B, C, and D, compete for two "slots" at a retail outlet. To keep things simple, assume that the retailer is a monopolist, that the manufacturers have the same costs, and that all manufacturers know that their rivals have the same costs.[29] Assume further that the four products are symmetric in the sense the retailer expects to make the same sales and earn the same profits regardless of which two products it carries.[30] Manufacturers compete to have their products stocked by announcing their wholesale prices. The retailer then selects the two products it will carry, sets retail prices, and pays the winning manufacturers the wholesale prices that they announced for each unit sold.[31]

This situation is analogous to an auction in which four identical bidders, (the four manufacturers) "bid" for two identical items (the two slots on the shelf). Since there are more bidders than items, and the bidders have complete information about their rivals, this auction will yield the perfectly competitive outcome. That is, the bidding process will result in a wholesale price equal to the manufacturers' marginal cost. Suppose that the winning bidders are manufacturers A and B. What is the elasticity of the derived demand facing manufacturers A and B?

To answer this question, we need to consider what would happen if one of the winning bidders attempted to raise its wholesale price. Suppose that manufacturer A did so. Because the losing bidders, C and D, each stands ready to sell a product with a sales and profit potential equal to that of product A, the retailer would respond to A's price increase by replacing product A with product C or D. That is, a wholesale price increase by manufacturer A would cause it to lose *all* of its sales. This means that the elasticity of demand facing the manufacturer A is very high (in this example, infinite), even though the elasticity of the consumer demand for product A could be very low. The reason for the large own elasticity for product A is the high cross elasticity between product A and other products C and D that are not currently carried by the retailer.[32]

Now consider the effects of a merger between the two winning bidders, A and B. After the merger, there will still be three independent firms bidding for two slots. The post-merger auction will still yield the competitive outcome, so the merger will have *no* effect on the wholesale price. Notice that this conclusion is independent of the own and cross elasticities of the *consumer* demand (i.e., the demand facing retailers) for the merging firms' products.

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[29] The insights from this example are relevant for more complicated markets.

[30] Note that this assumption does not mean that the products are homogenous. They could be differentiated or even independent products that have the same retail profit potential.

[31] In practice, competition for shelf space often involves more complicated payment schedules than simple linear prices (see the next section on nonlinear contracts). However, this simple example is rich enough to convey the point we want to make here.

This example shows that retail shelf-space constraints can have important implications for manufacturer-level demand elasticities. In (e.g., a slotting allowance)34. If the fixed fee is positive, the average payment declines with the amount purchased (quantity discount); if the fixed fee is negative, the average payment increases with the amount purchased (quantity premia). A wide range of fees exchanged by manufacturers and retailers affect the marginal and/or the fixed (or "inframarginal") payment from the retailer to the manufacturer. Examples include presentation fees (paid for the privilege of making a sales presentation); display fees (paid for special merchandising and the display of products);35 pay-to-stay fees (paid to have the retailer continue stocking and displaying a product); and failure fees (paid when a product does not meet expected goals). Other common components of nonlinear payment schedules include volume discounts, minimum and maximum purchase commitments, and liquidated damages.

The complication introduced by nonlinear payments goes beyond simply trying to draw inferences about derived demand elasticities from retail data. Competition in nonlinear payment schedules is fundamentally different from competition in per-unit prices. Perhaps the easiest way to see this is through a simple example, which is based on models examined by O'Brien and Shaffer (1997)[36] and Shaffer (1991). The example illustrates that nonlinear payment schedules can have important implications for the effects of mergers among upstream suppliers.

O'Brien and Shaffer consider a model in which two differentiated suppliers compete in nonlinear contracts to sell through a single retailer. The authors show that the equilibrium contracts involve nonlinear payments in which the *marginal* transfer price (the per-unit component) paid by the retailer for each unit purchased equals the manufacturer's marginal cost. For the special case of two-part tariff contracts, this means that the wholesale price equals the manufacturer's marginal cost. Thus, nonlinear pricing allows the upstream firms to avoid double-marginalization,[37] analogous to the well-known case of nonlinear pricing under bilateral monopoly.[38]

[34] Slotting allowances are payments from manufacturers to retailers to induce the retailer to shelve the product. The use of these fees is found throughout the food retailing industry. A related practice is that of "pay-to-stay" fees, which are made in periods subsequent to the initial stocking decision so that the retailer continues to shelve the manufacturer's products.

[35] Display fees are for special displays or favored placement. Examples include special end aisle displays, "display pyramids" (such as for 12-can boxes of soft drinks), and preferred position on shelves (e.g., eye-level for bread).

[36] See also Bernheim and Whinston (1998), who studied a similar model.

[37] "Double-marginalization" refers to the pricing distortion that occurs when a retailer adds its own (supra-competitive) mark-up to an upstream firm's own (supra-competitive) mark-up.

[38] A basic result in the economics of vertical control is that bilateral monopolists can avoid double-marginalization (cf. note 12) using two-part tariffs.

This result has important implications for the effects of upstream mergers when nonlinear

The literature on competition in nonlinear contracts in intermediate good markets is still developing.[40] More work needs to be done, both theoretical and empirical, before we will be in a position to say with confidence how nonlinear pricing alters the effects of horizontal mergers. As the literature continues to advance in this area, the best strategy for merger analysis is probably to continue to employ models that assume linear pricing. We have no empirical basis at this point for concluding that the predictions of these models are inherently biased one way or another. Our intuition is that models based on linear pricing will probably overstate the anticompetitive effects of horizontal mergers, because multi-product nonlinear pricing tends to eliminate double marginalization distortions (as suggested by the example above). However, the precise nature and importance of any bias awaits additional theoretical and empirical work.

VI. CONCLUSION

Economists have made substantial progress in applying econometric techniques to the analysis of horizontal mergers. As a commentator recently observed, econometrics has much to offer as to means for "illuminating critical issues in antitrust investigations and litigation."[41] In this paper, we have attempted to identify some aspects of this approach that could benefit from additional analysis and research by both academic and practicing antitrust economists. We do not intend to indicate that we believe that econometric analyses of scanner data are not useful. At the FTC we regularly conduct such analyses and have found them to be useful, when combined with the other evidence developed in a merger investigation. This paper, however, has highlighted issues that in some contexts are likely to require specific attention in assessing the viability and utility of the estimates.

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[40] The theoretical literature on buyer-specific nonlinear contracts has focused mainly on cases with oligopoly at either the upstream or downstream level and either a single seller or perfect competition at the other level. It has also focused on different issues than horizontal mergers. For example, O'Brien and Shaffer (1997) and Bernheim and Whinston (1998) examine incentives for exclusive dealing when the downstream firm is a monopolist. O'Brien and Shaffer (1992) and McAfee and Schwartz (1994) examine the role of vertical restraints and nondiscrimination clauses for a single supplier selling through competing retailers. Hart and Tirole (1990) consider buyer-specific contracting with duopoly at both stages, but they focus on the effects of vertical integration and exclusive contracts. There is no published empirical work on how to predict the effects of horizontal mergers when firms negotiate nonlinear contracts. An interesting step in this direction is taken by Villas-Boas (2001). She estimates the retail demand for yogurt using the discrete choice methodology of Berry (1994) and Barry, Levinsohn and Pakes (1995) and attempts to distinguish between different models of (linear and nonlinear) input pricing using a non-nested hypothesis test, as in Bresnahan (1987). Using this technique, it would be possible in principle to distinguish between different models of input pricing and to use that model to predict the effects of upstream mergers.

[41] Werden (2002), p. 47.

Bibliography

Abraham, Magid, and Leonard Lodish (1993). "An Implemented System for Improving Promotion Productivity using Store Scanner Data." *Marketing Science* 12 1993, 248-269.

Abrue, Dilip, Pearce, David, and Stacchetti, Enio (1986). "Optimal Cartel Equilibria with Imperfect Monitoring," *Journal of Economic Theory* 39, 251-69.

Bernheim, B. Douglas, and Michael Whinston (1998). "Exclusive Dealing," *Journal of Political Economy*, 106, 64-103.

Berry, Steven *et al.*(1995). "Automobile Prices in Market Equilibrium," *Econometrica*; 63, 841-90.

Berry, Steven (1994). "Estimating Discrete Choice Models of Product Differentiation," *Rand Journal of Economics* 25, 242-62.

Bertrand, Joseph (1883). Review of "Theorie Mathematique de la Richess Sociale" and Recherche sur les Principes Mathematiques de la Theorie des Richesses." *Journal de Savants*, 499-508.

Bresnahan, Timothy (1987). "Competition and Collusion in the American Automobile Industry: The 1955 Price War," *Journal of Industrial Economics* 35, 457-82.

Bresnahan, Timothy (1997). "Valuation of New Goods under Perfect and Imperfect Competition: Comment," in Bresnahan, Timothy and Gordon, Robert J., eds. *The Economics of New Goods: NBER Studies in Income and Wealth vol. 58.*, 237-47.

Bresnahan, Timothy (1997). "The Apple Cinnamon Cheerios War: Valuing New Goods, Identifying Market Power, and Economic Measurement," mimeo.

Brownstone, David and Robert Valletta (2001). "The Bootstrap and Multiple Imputations: Harnessing Increased Computing Power for Improved Statistical Tests," *Journal of Economic Perspectives* 15, 129-41.

Capps, Oral, *et al.* (2001), "Specification Issues and Confidence Intervals in Unilateral Price Effects Analysis," mimeo.

Cournot, Augustin (1987). *Researches sur les Principes Mathematiques de la Thoery des Richesses.* English edition (ed. N. Bacon): *Researches into the Mathematical Principles of the Theory of Wealth*. New York: Macmillan.

Crooke, Phillip *et al.* (1999). "Effects of Assumed Demand Form on Simulated Postmerger Equilibria," *Review of Industrial Organization* 15, 205-17.

Deaton, Angus, and John Muellbauer (1980). *Economics and Consumer Behavior*.

Efron, Bradley and Robert Tibshirani (1993).

Hausman, Jerry and Gregory Leonard (2000). “The Competitive Effects of a New Product Introduction: A Case Study,” Mimeo, MIT.

Hendel, Igal and Aviv Nevo (2001). “Sales and Consumer Inventory.” unpublished manuscript.

Hoch, Stephen, Byung-Do Kim, Alan Montgomery, and Peter Rossi (1995). “Determinants of Store-Level Price Elasticity.” *Journal of Marketing Research* 23, 17-29.

Horn, Heinrick, and Asher Wolinsky (1988). “Bilateral Monopolies and Incentives for Merger,” *Rand Journal of Economics*, 19, 408-419.

Hosken, Daniel, and David Reiffen (1999). “Pricing Behavior of Multiproduct Retailers” *Federal Trade Commission Bureau of Economics Working Paper* 225

Irwin, Douglas, and Nina Pavcnik (2001). “Airbus Versus Boeing Revisited: International Competition in the Aircraft Market,” mimeo. (http://www.dartmouth.edu/~npavcnik/Research_files/airbus.pdf).

Katz, Michael and Carl Shapiro (1986). "Consumer Shopping Behavior in the Retail Coffee Market," in P. Ippolito and D. Scheffman (eds.) *Empirical Approaches to Consumer Protection Economics*, FTC, March 1986, 415-443.

Koenker, Roger, and Kevin Hallock (2001). “Quantile Regression,” *Journal of Economic Perspectives* 15, 143-56.

Maskin, Eric and Jean Tirole (1987). “A Theory of Dynamic Oligopoly, III: Cournot Competition,” *European Economic Review* 31, 947-68.

Maskin, Eric and Jean Tirole (1988a), “A Theory of Dynamic Oligopoly I: Overview and Quantity Competition With Large Fixed Costs,” *Econometrica*, 56, 549-69.

Maskin, Eric and Jean Tirole (1988b), “A Theory of Dynamic Oligopoly II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles,” *Econometrica,* 56, 571-99.

Montgomery, Alan (1997). “Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data.” *Marketing Science* 16, 315-337.

Nash, John F. (1950). “Non-cooperative Games,” *Econometrica,* 18, 155-62.

Nevo, Aviv (2000). “Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry,” *Rand Journal of Economics*, 31, 395-421.

Nevo, Aviv (2001). “Measuring Market Power in the Ready-to-Eat Cereal Industry,” *Econometrica*, 69, 307-342.

McAfee, R. Preston, and Marius Schwartz (1994). “Opportunism in Multilateral Vertical Contracting, Nondiscrimination, Exclusivity, and Uniformity,” *American Economic Review*, 84, 210-30.

Novshek, William (1980). “Cournot Equilibrium with Free Entry,” *Review of Economic Studies*, 47, 473-86.

O’Brien, Daniel P. and Greg Shaffer (1992). “Vertical Control with Bilateral Contracts,” *Rand Journal of Economics*, 23, 299-308.

O’Brien, Daniel P. and Greg Shaffer (1997). “Nonlinear Supply Contracts, Exclusive Dealing, and Equilibrium Market Foreclosure,” *Journal of Economics & Management Strategy*, 6, 755-785.

Pakes, Ariel and McGuire, P. (1994). “Computing Markov-Perfect Nash Equilibrium: Numerical Implications of a Dynamic Differentiated Product Model,” *Rand Journal of Economics*, 25, 555-589.

Pesendorfer, Martin (2002). “Retail Sales: A Study of Pricing Behavior in Super Markets,” *Journal of Business* 75, 33-66.

Pinkse, Joris and Slade, Margaret (2001). “Mergers, Brand Competition, and the Price of a Pint,” Mimeo, Department of Economics, University of British Columbia.

Pinkse, Joris, Slade, Margaret and Craig Brett (2002). “Spatial Price Competition,” *Econometrica*, forthcoming.

Reiss, Peter and Matthew White (2001). “Household Electricity Demand, Revisited,” *National Bureau of Economics Working Paper #8687*

Shaffer, Greg (1991). “Capturing Strategic Rent: Full-Line Forcing, Brand Discounts, Aggregate Rebates, and Maximum Resale Price Maintenance,” *Journal of Industrial Economics* 39, 557-75.

Shapiro, Carl (1989). “The Theory of Business Strategy,” *RAND Journal of Economics* 20, 125-37.

Slade, Margaret (2001). “Assessing Market Power in UK Brewing,” Department of Economics, The University of British Columbia, Discussion Paper No. 01-04, March 2001.

Steiner, Robert L. (1973). “Does Advertising Lower Consumer Prices?” *Journal of Marketing*, 37(4).

Steiner, Robert L. (1993). “The Inverse Association Betw

Wolfram, Catherine (1999). “Measuring Duopoly Power in the British Electricity Spot Market,” *American Economic Review*, 89, 805-26.