Econometric Issues in Antitrust Analysis

by

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This paper critically views a number of econometric methods that have been utilized in investigations by competition agencies and in private litigation. The focus is on market definition and unilateral competitive effects. Specific topics include critical-loss analysis, price-correlation analysis, merger simulation, and difference-in-differences analysis. When used appropriately and with caution, each of these methodologies can be of substantial value. (JEL: L 40, K 41)

1 *Introduction*

The use of econometric methods to study competitive issues, especially those relating to mergers, has been continually expanding in recent years, both in the United States and in the European Union. With respect to the public enforcement agencies, econometric techniques have been used in the analysis of market definition, the evaluation of unilateral competitive effects relating to mergers, and in the non-merger context, with respect to the analysis of network effects, market structure, and exclusionary practices. Finally, in the United States, econometric methods have frequently appeared in private antitrust cases, when there were issues relating to class certification and to damages.

In this paper, I review some of the econometric methods that have been utilized in the context of investigations by the competition agencies and in private litigation. My focus will be on market definition and unilateral competitive effects. I will emphasize the potentially valuable application of relatively new methods such as cointegration analysis and difference-in-differences analysis.

2 *Market Definition*

The exercise of market power requires that the firm or firms involved (collectively) face a relatively inelastic demand curve for a product at "competitive" prices. Only then can it be profitable for firms to raise price by reducing output. There is currently some controversy as to whether it is appropriate to focus initially on

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demand when defining relevant antitrust markets, or whether one should incorporate both supply and demand elements in the analysis. The European Union appears to be taking the latter approach, whereas the U.S. competition agencies have taken the former.

2.1 Using the DOJ/FTC Merger Guidelines

If market definition analysis is to be utilized, I believe that the demand-side focus of the U.S. Horizontal Merger Guidelines offers the most sensible way to proceed. There is sufficient complexity as to how one should undertake the analysis of demand, without further complicating the analysis by considering the timeliness and sufficiency of entry on the supply side.

Identifying and estimating the relevant demand elasticities can be a difficult exercise, and this is where a number of econometric issues come to the fore. It is thought by some that the market definition exercise only be accomplished when evaluating mergers in industries that generate substantial micro-level data, such as IRI or Nielsen scanner data. However, as BAKER AND RUBINFELD [1999] have described in detail, this is not the case. There are numerous methods for identifying the structure of demand, some of which do not require extensive data. Moreover, even in situations in which past experience is not sufficient to allow one to identify demand econometrically, conjoint survey methods offer a potentially valuable alternative approach.

A related issue surrounds the use of the SSNIP test in the analysis of relevant markets. According to the U.S. Horizontal Merger Guidelines (brackets added),[1]

> "Absent price discrimination, the Agency will delineate the product market to be a product or group of products such that a hypothetical profit-maximizing firm that was the only present and future seller of those products ('monopolist') likely would impose at least a 'small but significant and nontransitory' increase in price." [the "SSNIP test"]

A relevant market is:

> "[a] group of products and a geographic area that is no bigger than necessary to satisfy this test." [the "smallest market" principle]

While most would agree that the SSNIP test is conceptually valuable, there are many situations in which a complete SSNIP approach is not workable, either because of data limitations or because the market is so highly differentiated that there is no clarity as to the order in which products should be added if the initial hypothetical relevant market is not sustainable. While a good deal has been written about this subject, the U.S. Merger Guidelines are largely silent.

As guidelines are developed in the E.U. and as the revision of the U.S. Merger Guidelines is a possibility, we should be cognizant of the fact that even when a full

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[1] U.S. Department of Justice and the Federal Trade Commission, *Horizontal Merger Guidelines*, § 1.1, revised April 8, 1997.

implementation is not possible, the Guidelines teach us to be careful in evaluating documentary evidence or evidence obtained through surveys. Marketing studies are often informative with respect to the list of possible products that might be included in a relevant market, but it is only occasionally the case that such studies offer sufficient information about demand elasticities to be of immediate, direct use. Similarly, posing direct questions to consumers as to whether they would switch in response to a hypothetical price increase, without the context and implicit budget constraint that is part of a conjoint study, does not usually offer the best information about demand substitution.

2.2 *Uncovering the Structure of Demand*

The great promise of econometric methods is that they permit a systematic synthesis of the quantitative evidence, weighing the most informative data the heaviest. BAKER AND RUBINFELD [1999] outline a variety of methods that can be used to uncover the underlying demand structure associated with a particular merger or non-merger analysis. One can estimate demand systems using market data, at the micro level (e.g., through the use of scanners) or at an aggregated level, using wholesale or retail price indices. Sometimes, however, the available data are not conducive to the direct estimation of demand elasticities. Alternative methodologies may then offer ways to learn about consumer preferences. These methods include (i) the use of auction models to make inferences from bidding information;[2] (ii) inferring preferences from an analysis of the attributes of the goods and services that consumers purchase;[3] and (iii) eliciting preferences from survey responses to hypothetical questions involving product attributes (conjoint analysis).[4]

As a theoretical matter, if there are sufficient data and one is comfortable making the assumptions that are necessary to estimate a complete demand structure, the market definition exercise put forward by the Merger Guidelines is readily workable. The own price elasticity of demand offers the most direct approach to market definition. One can determine immediately from the shape of the demand curve whether a price increase by a hypothetical monopolist would be profitable. However, it is worth noting that there are cases in which cross-price elasticities provide useful information. Cross-price elasticities can be informative as to whether particular products should or should not be in the market, and more generally as to the order in which products should be added as the size of the proposed market is increased. In each case, cross-price elasticities tell us the magnitude of switching that will

2 For the use of auction models to analyze bid rigging, see PORTER AND ZONA [1993], [1999]; for accounting mergers see SULLIVAN [2002]; for hospital contracts see DALKIR, LOGAN, AND MASSON [2000].

3 See, for example, BERRY, LEVINSOHN, AND PAKES [1995] and NEVO [2000].

4 Conjoint analysis supported the consent decree in *U.S. and the State of Colorado v. Vail Resorts, Inc. et al.* (1/22/97) and was put forward (but eventually excluded) in *U.S. v. Dentsply* (U.S. District Court for the District of Delaware, Civil Action 99-005).

occur in response to the hypothetical price increase. (The own price elasticity will be equal to a weighted sum of all of the cross-price elasticities.)

When evaluating switching questions, the diversion ratios provide useful information. Suppose, for example, that we wish to look at whether product Y is substitutable for product X. We simply multiply the cross-price elasticity of Y with respect to X by the pre-merger quantity of Y to obtain ΔY, the quantity of Y diverted by an increase in the price of X. Then, the diversion ratio, $\Delta Y/\Delta X$ is the proportion of the diversion in X that goes to Y.

When the complete determination of a demand system cannot be accomplished (whether through the use of econometrics or otherwise), there are several alternative approaches that have been proposed. Two are worthy of particular comment – critical-loss analysis and the use of price correlations. I discuss each in the subsections that follow.

2.3 *Critical-Loss Analysis*

In its simplest form, critical-loss analysis proceeds as follows. The critical loss is the maximum diversion of sales that will still sustain a profitable price increase by a hypothetical monopolist in a putative relevant antitrust market. Any actual loss that is higher than the critical loss will make the price increase unprofitable, thus making it necessary (following the smallest market principle) to increase the scope of the relevant market.

To calculate the critical loss, let P represent the current price of the hypothetical monopolist, $\Delta P/P$ the proposed percentage price increase (often 5%); MC the marginal (incremental) cost of production, and m the percentage profit margin of the hypothetical monopolist. Also, let $(P - MC)/P$, Q represent the sales volume of the hypothetical monopolist, and ΔQ the lost sales volume (diversion).

Then it is not difficult to show that the critical loss, CL, is given by the following formula:

$$CL = (\Delta P/P)/(\Delta P/P + m)\,. \tag{1}$$

Critical-loss analysis is an appealing approach because of its apparent simplicity. It has been used a number of times by the competition agencies and by the courts.[5] To obtain the critical loss (at least in this simple case), we begin by choosing a hypothetical price increase and estimating the profit margin associated with the product in question. Of course, this is not always a straightforward exercise. While 5% is a typical assumption for the hypothetical price increase, the appropriate increase should be selected on a case-by-case basis, since it is a function of the nature of competition in the industry. To illustrate, the Federal Trade Commission has used a smaller hypothetical price increase when analyzing grocery store or

[5] See, for example, the *Sungard* case, in which the Department of Justice failed in its attempt to block the acquisition of ComDisco; the decision is at 172 F. Supp. 2d 172 (2001).

supermarket mergers, since the industry is one in which margins are historically quite low.

The appropriate variable profit margin is given by the incremental profit for the hypothetical monopolist. Even if one is willing to assume that the monopolist's costs would be identical to that of the firm or firms involved in the merger, there still remains the problem of deriving a margin estimate from the profit and loss statements of the firms. Often these statements will not break down profitability on a product-by-product basis. Furthermore, the accounting decisions as to which costs are fixed and which are variable will not always replicate the decisions that economists would make (see FISHER AND MCGOWAN [1983]).

The crucial tension associated with critical-loss analysis flows from the problem of estimating the actual loss. An accurate prediction of this loss necessitates reliable estimates of the parameters of the appropriate demand system. It is difficult to obtain estimates of actual loss from documentary evidence or from direct testimony. In most critical loss analyses, the critical loss will be relatively small; for example, if one is utilizing a 5% hypothetical price increase and the profit margin is 30%, the critical loss will be 14.3% (if the profit margin is 50%, the critical loss falls to 9.1%).

It is worth noting that high variable profit margins, which imply relatively low critical losses, do not by themselves imply that markets should be broadly defined. A high profit margin can be enjoyed by firms because the market demand is relatively inelastic (see PINDYCK AND RUBINFELD [2009, Ch. 10]). Inelastic demand, in turn, implies that the actual loss, other things equal, is also likely to be relatively small. On balance, therefore, one cannot draw any immediate inference concerning market definition from the magnitude of the critical loss.

It is not unusual in merger cases for the parties to the merger and the competition agencies to obtain affidavits from customers saying that the customers would switch (the affidavits obtained by the parties) or would not switch (the affidavits obtained by the agencies) in response to the price increase. However, the process is inherently subject to selection bias. The parties have an incentive to offer testimony from those who would switch, whereas the agencies have the opposite incentive. Unless the volume of customer sales represented by this sort of testimony represents a large volume of sales or one can show that the offer of testimony was not subject to selection bias, the resulting body of evidence is not likely to be dispositive.

To sum up, critical-loss analysis provides a useful conceptual exercise, since it poses the right question with respect to market definition. However, the extensive debate about pros and cons associated with the use of critical-loss analysis suggests that it must be applied with care and diligence.[6]

[6] See KATZ AND SHAPIRO [2003], O'BRIEN AND WICKELGREN [2003] and the articles cited therein.

2.4 *Price-Correlation Analysis*

A longstanding ad hoc approach to market definition flows from the early work of Stigler and Sherwin (STIGLER AND SHERWIN [1985]). The authors propose an analysis of the correlations among various goods or services thought to be in the same market. If the price correlations among two or more goods are sufficiently high, this is seen as providing supporting evidence that the goods are in the same market.

I find the examination of price movements and correlations to be a useful exercise. However, it is well known that such a price-correlation analysis is flawed (see WERDEN AND FROEB [1993]). First, there is no useful rule that determines the appropriate cutoff describing when the correlation is sufficiently high to support two products being in the same market. Second, correlations are substantially affected by the presence of trend in the data. There may be no causal link between the prices of two goods whose correlation if high simply because both price series are substantially trended.

Cointegration analysis offers an improvement over the Stigler-Sherwin approach. Cointegration methods provide tests to see if two price series share a long-run relationship, even though that relationship may be masked by noise in the randomness in the variables.[7] Cointegration methods also help one to avoid concluding that two products are in the same market simply because the prices of both products are highly trended. If after removing trend (most often by working with the first differences of the price series rather than the series themselves) to obtain *stationary* price series, the two series are highly correlated, one can be more comfortable concluding that they are likely to be in the same market.

Suppose, however, that two price series are non-stationary. Typically, the sum of the two time series will also be non-stationary. However, there are occasions when the two variables will be *cointegated* and should still be considered likely to be in the same relevant market. This occurs when a weighted average of the two variables is stationary (e.g., one variable follows an unusual path, perhaps with trend, but the other variable follows a similar path). To sum up, if regression analysis is to be used to evaluate whether two products are in the same market by examining the relationship between several variables, it is necessary (but not sufficient) that the variables be either individually stationary and highly correlated or cointegrated.

Cointegration methods have been used in antitrust analysis generally, and by the European Union in particular, but the application of the methods has generally been limited to this point.[8] Indeed, it is important to note that like any statistical procedure,

[7] The cointegration methodology was developed by ENGLE AND GRANGER [1987]. See PINDYCK AND RUBINFELD [1998] for a brief overview. For a discussion of its applicability in antitrust analysis, see RUBIN [2004].

[8] Examples include MOLLGAARD AND NIELSEN [2004] and DE VANY and WALLS [1993] and MICHAELS AND DE VANY [1995]. See also, the European Commission's Decision of October 17 2001, which found a merger inconsistent with the common market (Case No. OMP/M.2187-CVC/Lenzing, available at http://europa.eu/int/comm/competition/mergers/cases/decisions/m2187_en.pdf.

cointegration does not resolve all of the concerns expressed above. Absent a valid theory of the structure of demand, one cannot rule out with certainty the possibility that two unrelated series will appear to be cointegrated and will wrongly be assumed to be in the same market.

3 *Unilateral Effects*

3.1 *Introduction*

Unilateral effects arise in the merger context when the merging entity finds it profitable to raise the price of one or more of its products because the merger has allowed the firm to internalize some of the sales that would have been diverted to a competitor had the merger not taken place. Unilateral effects analyses have been frequently used as the foundation for proceedings brought by the competition agencies. However, there continues to be some controversy over the pros and cons associated with various approaches that might be used to measure the extent, if any, to which unilateral effects are likely to occur. In the remainder of this section, I comment on two potentially reliable regression-based methods: merger simulation and difference-in-differences analysis.

3.2 *Merger Simulation*

Merger simulation is a set of quantitative techniques that are used to predict price effects of mergers in markets with differentiated goods. Applied to unilateral-effects analysis, merger simulation has been used to assess the magnitude of the merger-specific efficiencies (reductions in marginal costs for the merging firms) required to offset predicted price increases and to evaluate the adequacy of proposed divestitures. Simulation can also help one to analyze the competitive effects of product repositioning and de novo entry. Simulation methods are continuing to be developed and the scope of their possible application is being broadened. Yet, there has been substantial criticism and a plea for care in applying simulation only when the appropriate foundation has been laid.[9]

Merger simulation analysis is carried out in two stages. In the first stage, the estimation of a demand model provides own and cross-price elasticities of demand for the goods in the pre-merger market. In the second stage, one solves the first-order conditions (FOCs) for post-transaction profit maximization by the new, post-merger entity. The standard approach in current work is to assume Bertrand competition with constant marginal costs of production.[10] The post-transaction FOCs differ

[9] See, for example, WERDEN, FROEB, AND SCHEFFMAN [2004].

[10] The Bertrand pricing assumption is standard in existing models; it is analytically tractable and has been found to have empirical support. But when applying merger simulation to wholesale markets, one must think carefully before accepting the Bertrand pricing assumption. For example, a Bertrand equilibrium determined by continuously differentiable first-order conditions may not adequately describe wholesale

because they take into account both the cross-price elasticities between the two merging firms and the merger-specific efficiencies. Moreover, the demand model implies new elasticities as prices change in the new equilibrium. The solution finds the new post-transaction prices that are consistent with all of these effects.

Within the world of merger simulation, there is substantial debate concerning the choice of demand model. The more sophisticated and complex the demand model, the more likely it is that an appropriated calibrated model can give accurate predictions of the price effects of a merger. (This presumes, of course that the merger does not change the nature of the strategic interaction among firms. If there is such a change, merger simulation is unlikely to be the appropriate methodology.)

Sophisticated demand estimation requires not only substantial data, but also significant calendar time. In the context of an active proposed merger, both data and time limitations can be crucial. For this reason, I find the use of less complex models to often be advantageous. If one is comfortable with the underlying assumptions that support the simpler models, useful merger simulations can be carried out relatively quickly and without the necessity of putting together a large dataset. My own sentiment lies towards simplicity, which is what provided the motivation for my joint work with Roy Epstein in producing a merger simulation methodology that can be applied utilizing a Microsoft Excel spreadsheet.[11]

To get a sense of the tradeoffs involved with the various merger simulation methods, it will be useful to describe four alternative demand models: (i) the BERRY, LEVINSOHN, AND PAKES [1995] version of the random coefficients logit demand model ("BLP"), (ii) the Almost Ideal Demand System advocated by HAUSMAN, LEONARD, AND ZONA [1994] ("AIDS"), (iii) the antitrust logit model espoused by WERDEN AND FROEB [1994] ("Logit"), and (iv) the proportionality-calibrated AIDS model, or "PCAIDS," developed by EPSTEIN AND RUBINFELD [2001]. Each model should be viewed as an approximation to the "true" underlying structure. The models differ in their data requirements, the difficulty in calibration, the flexibility in representing price elasticities, and the bottom-line predictions of price changes. BLP is the most complex and the most demanding, while PCAIDS is the least complex and the easiest to apply.[12]

A brief background discussion will provide a useful perspective on the tradeoffs involved in choosing among the various demand models. The estimation of any general formulation of a demand model involving numerous products will require a large number of parameters to be estimated. The central methodological question is how to specify a simplified model that is tractable and has good predictive power. A related problem is that consumer tastes for differentiated products are likely to

markets where a large fraction of output is sold in a small number of "winner take all" auctions.

[11] See EPSTEIN AND RUBINFELD [2004a], [2004b, pp. 28–44] for detailed descriptions of the PCAIDS model.

[12] For a useful overview of these methods, see the merger simulation chapter in HARKRIDER AND RUBINFELD [2005].

be heterogeneous; otherwise, we would not see differentiated offerings in the first place.

The random coefficients logit model builds on a discrete choice model of utility maximization in which the analyst specifies the utility function that underlies the demand model. This approach reduces the complexity of the most general demand model (i.e., reduces the dimensionality) by assuming that consumer demands can be described in terms of a modest number of underlying product characteristics. If demand can be characterized in terms of an appropriate set of characteristics, the random coefficients model can be estimated using either individual-level or market level data.

As a practical matter, the BLP application of the random coefficients model is particularly advantageous because it can be estimated using only market level data and because it appears (to NEVO [2000] and others) to give more accurate price predictions. However, BLP suffers from the disadvantage that the demand estimation involves maximum-likelihood estimation, which can be difficult to apply, and because the success of the model depends crucially on the choice of an appropriate set of product characteristics.

The AIDS model starts with a functional form specification of the demand model, and as a consequence is less complex and demanding than the BLP model. Nevertheless, AIDS requires detailed consumer level price and revenue information, which for many consumer goods mergers are supplied by scanner data. Because it can require the estimation of dozens of coefficients, estimating an AIDS model can be a significant econometric challenge. The goal is to obtain a complete set of coefficients with plausible algebraic signs, magnitudes, and statistical reliability. Advocates of the random coefficients model find the possibility of "wrong" signs associated with cross-price elasticities in the AIDS model (suggesting that competing goods are complements rather than substitutes) to be very troublesome. I find this issue less disturbing than some – given the complex nature of price changes in some markets and given that demand estimation usually is restricted to a relatively short time period, an occasional "wrong" sign does not seem problematic.

The antitrust logit model offers substantially greater simplicity than either the BLP or AIDS models. In its simplest form, this logit model requires only market shares, a measure of substitutability between products, and an estimate of the market demand elasticity. As a tradeoff for the relative simplicity of its inputs, the logit model relies upon the relatively strong assumption that the cross-elasticities are identical across products.[13] Advocates of the random coefficients model find the antitrust logit model to be limiting, since the elasticity assumptions will not always be appropriate in mergers involving differentiated products.

The PCAIDS model offers a simplified version of AIDS that is similar in its data requirements to the basic logit model. PCAIDS requires only market shares, an estimate of the market's demand elasticity, and an estimate of the price elasticity of demand for one product involved in the merger. Like the logit model, PCAIDS as-

[13] The nested logit model relaxes this assumption.

sumes in its most basic form that cross-price elasticities between competing products are equal. PCAIDS and the logit model differ in their underlying demand curvature, which leads to different predictions of unilateral effects. When the assumption of identical cross-price elasticities for each product is not appropriate, both the basic logit model and PCAIDS can be generalized by introducing additional "nesting parameters" to make the demand model more flexible.

The PCAIDS and logit models yield different estimates of price effects since elasticities change along the underlying demand curves as prices increase. Own-price elasticities increase and cross-price elasticities will also change. Even if all models are matched to the same set of pre-merger elasticities, the predicted post-merger prices will depend on the specifics of the mathematical relationships that define the demand system.

Ultimately, the issue of whether the benefits of merger simulation outweigh the costs remains an open one, as is the specification of the particular conditions under which each particular model is likely to be most effective. A number of recent studies have begun to offer some interesting answers to these questions. One particularly interesting study, PETERS [2006], uses merger simulation methods to predict post-merger prices for five airline mergers (Northwest-Republic, TWA-Ozark, Continental-People Express, and Delta-Western).

Peters suggests that merger simulation methods do not fare well. However, a careful reading of this paper shows that the author's primary criticism goes to the failure of merger simulation models to account for supply-side effects and for more flexible models of firm conduct than the basic Bertrand model. Either can be accounted through merger simulation if a more sophisticated model is adapted. Moreover, Peters utilizes only two demand models, and so does not offer a comparative analysis of the efficacy of a wider range of alternative demand models.[14]

It is worth reiterating that complexity typically costs at a cost, in terms of the calendar time needed to estimate the demand model, and in terms of the data demands. Furthermore, merger simulation may be much more effective in analyzing the price effects of mergers in industries other than airlines, where the traditional static non-cooperative oligopoly model may not offer the best characterization of competition.

3.3 Difference-in-Differences Analysis

When undertaking a unilateral-effects analysis of a merger, the most desirable source of useful information comes from natural experiments that have arisen in the past. These might involve changes in relative prices, changes in capacity, or changes in the number of competitors in the industry (through entry and exit). While this approach has been used frequently by the competition agencies, the number of litigated cases remains relatively small. Among the more interesting litigated cases are *State of New*

[14] The two models include a basic logit model and the generalized extreme value (GEV) variant of the random coefficients logit model of BRESNAHAN, STERN, AND TRAJTENBERG [1997].

York v. Kraft General Foods (the merger of two ready-to-eat cereal companies), *FTC v. Staples Depot* (the proposed merger of two office superstore chains), and *FTC v. Whole Foods* (the proposed merger of two high-end supermarket chains).[15]

In each of these cases one of the central questions related to market definition. The question at issue was whether a particular product "category" can appropriately be characterized as a separate relevant market. The plaintiffs' proposed market in *Kraft* was "adult cereals," in *Staples* "consumable office products supplied by office superstores," and in *Whole Foods* it was "premium, natural, and organic supermarkets." The key issue in each case was whether retailers in each of the proposed markets were more constrained by *intra-category* competition than by *inter-category* competition.

In each of these cases, further issues were raised as to the likelihood that there would be unilateral anticompetitive effects. *Staples* offers a useful example. The Federal Trade Commission provided evidence that prices in two-office-superstore cities were seven percent lower than in one-office-superstore cities. The evidence came in the form of simple comparisons of means and in the form of a more sophisticated regression analysis that attempted to control for factors not-related to price changes. While the regression analysis attempted to replicate a natural experiment, the reality was a quasi-experiment in which a number of factors unrelated to changes in price were varying across cities and over time.

It is natural to ask: What is the best experimental design for such a quasi-experiment? One promising answer lies in difference-in-differences analysis (DID). As it would be applied in *Staples*, the basic DID design divides the subjects of study (e.g., firms) into a "treatment group" and a "control group." The treatment (e.g., a reduction in the number of competitors) is applied to the treatment group (e.g., cities in which the merger reduces the number of competitors) and the average outcome (e.g., the resulting average price) associated with the treatment control is compared to the control group (the average prices in cities with no change in the number of competitors). If the outcome in the treatment group is different, we conclude that the treatment has had a causal effect on the outcome, e.g., a reduction in the number of superstore competitors has raised prices of office products in superstores.

If the treatment had been randomly assigned as in a real experiment, we would not have needed to control for other factors. However, in the real world of quasi-experiments there is no random assignment, and multiple regression is typically needed to control for other factors. Because we do not have an ideal experiment, and we typically cannot observe the counterfactual (what if a store had not closed or opened in a market?), a number of econometric issues are raised; these include the possibilities of selection bias, omitted variable bias, and simultaneity. In the

[15] *State of New York v. Kraft General Foods, Inc.*, 926 F.Supp.321 (S.D. N.Y. 1995), *Federal Trade Commission v. Staples*, 970 F.Supp.1066 (D.D.C. 1997), and *Federal Trade Commission v. Whole Foods Markets, Inc.*, Civil Action 07-1021 (2007). For an analysis of the cereal merger, see RUBINFELD [2000]. For a discussion of the *Staples* case, see BAKER [1999].

discussion that follows, I briefly describe DID analysis. Following this, I discuss the conceptual problems, and I survey a few recent applications of DID analysis in antitrust cases.

To begin a discussion of DID, we might compare the mean of each group's outcome (e.g., average price) with and without treatment. If we let P_B be the mean price before treatment and P_A the mean price after treatment, then the treatment effect would be given by $(P_A - P_B)$. In the regression framework, we would estimate the model

$$P_i = \alpha_0 + \alpha_1 TRT_i + \varepsilon_i \, , \tag{2}$$

where $TRT = 1$ if in treatment group, $= 0$ if in control group. In this case, α_1, the *differences estimator*, measures the treatment effect (assuming that $E(\varepsilon_i | TRT) = 0$).

The problem with this simple differences estimate is that some of the unobserved variables might be persistent over time, and there might be pre-treatment differences in P among various groups. DID has the potential to do better. To describe DID analysis, let C_B represent the mean price in the control group before the treatment is put into effect, and let C_A represent the mean for the control group after the treatment. Then, the DID estimate of the treatment effect is given by $(P_A - P_B) - (C_A - C_B)$. In the regression context (we can add additional covariates as appropriate), the model is given by

$$P_i = \beta_0 + \beta_1 TRT_i + \beta_2 AFT_i + \beta_3 TRT_i \times AFT_i + \varepsilon_i \, , \tag{3}$$

where $AFT = 1$ if after treatment, $= 0$ if before, and $E(\varepsilon_i | TRT, AFT) = 0$. In this case, the coefficient on the interaction term (β_3) measures the DID estimate of the treatment effect.

DID is potentially a useful, indeed powerful approach to the analysis of unilateral effects. It removes the possible bias that might result if one were to use a simple differences estimator. For example, suppose that TRT is correlated with P, i.e., there are pre-treatment differences in price between those that will receive the treatment and those that will not. If $P_A > P_B$, and $C_A > C_B$, then the differences estimator will mistakenly overvalue the success of the treatment, since the treatment group had better outcomes than the control group before the treatment was applied. By accounting for factors that affected controls pre-treatment, the DID estimator removes this source of bias.

To see how DID might work in the antitrust context, reconsider the Staples-Office Depot merger. There are two possible differences analyses that might have been undertaken: (1) a comparison of average prices in cities with two stores versus average prices in cities with one store at the same point in time; and (2) a comparison of average prices over time in cities in which entry and exit have occurred. The DID analysis does both in the context of a single regression model with interactions.

As a second example, consider the recent proposed merger of Whole Foods and Wild Oats. After a lengthy trial in Federal District Court, the Court ruled against the Federal Trade Commission and allowed the merger to proceed (the court did not grant an injunction pending the appeal of the case). In the District Court trial, Whole

Foods expert, David Scheffman, relied in part on a critical-loss analysis, while the FTC's expert, Kevin Murphy, relied in part on an analysis of the relationship between entry and profitability. Neither was able to undertake a DID analysis, presumably because the conditions approximately an ideal natural experiment were not present.

On appeal, the D.C. Circuit ruled for the FTC and remanded for a new trial. Just prior to the scheduled trial date the case settled. Had the case proceeded to trial, it would have been natural for the parties to present a DID analysis of the natural experiment that arose after Whole Foods consummated the merger up until the settlement of the case.

DID analysis was also used by BAMBERGER, CARLTON, AND NEUMANN [2004] in their retrospective analysis of the effect of airline alliances on airline fares. In the framework of the paper the treatment was given by two Alliances: Continental/America West and Northwest/Alaska. The controls were (i) the presence of Southwest Airlines, (ii) the percentage of passengers flying direct, and (iii) market concentration. The authors concluded that average fares fell from 5–7% as a result of the alliances.

The advantages of a DID analysis can be summarized as follows. DID removes the bias that can flow from a cross-section analysis that fails to account for other systematic differences across cities. DID also removes the bias that can flow from a purely time-series analysis that fails to account for systematic factors that changed over time. Differencing across time within a city eliminates the effects of local market conditions other than entry. Differencing across cities within a time period eliminates the effects of common factors that could affect a study of entry.

Unfortunately, DID analysis does not remedy all possible ailments. First, the choice of control variables in the regression model can matter. The addition of more covariates (as controls) in the regression can improve the precision of the model if the movements of the control variables are reasonably correlated with the treatment group. However, a control that is affected by the treatment can bias the estimates associated with the analysis. Thus, DID analysis does not eliminate the usual regression model specification tradeoff between bias and efficiency.

Second, if the treatment is not randomized, ε will not be independent of *TRT* and *AFT*. Outcomes will be affected both by the treatment and by the effect of non-random assignment, and the results will be biased. Third, if the effect of the treatment was not the same for all members of the treatment group (heterogeneity) due, for example, to partial compliance, the key parameter estimates will be biased (the causal effect will vary from individual to individual).[16] Fourth, if the treatment is randomly assigned, then, DID will measure the average treatment effect. However, if the treatment is only partially randomly determined, as in many quasi-experiments, then

[16] It is also possible that the effect of entry might be different from the effect of exit. Alternatively, the effects of entry and exit might be felt over some period of time; if so, a more complex DID specification will be required (in the first case involving additional interaction terms and in the second case requiring a dynamic demand specification).

instrumental variables estimation may be necessary to deal with any simultaneity that might be present.

In any DID analysis, it is natural to ask what would have happened to the non-treatment group had there been no treatment? One possible answer comes from adding additional covariates to the regression model. If one does so, however, it is important to ask whether *TRT* is correlated with characteristics of those receiving treatment. If it is, the inclusion of the additional covariates may bias the parameter estimation.

There are further, somewhat more complex issues that flow from DID as well. It is often the case that DID will use a regression model that includes several years of serially-correlated data. When doing so, it is essential to correct the tests of statistical significance to reflect the bias in the classical tests that result without the adjustment (see BERTRAND, DUFLO, AND MULLAINATHAN [2004]).

4 Concluding Remarks

The use of econometric analysis in antitrust analysis has been growing worldwide, and the quality of that analysis has improved as well. However, along with the increasing sophistication of the methodologies that have been used have come a number of unsettled issues. In this article, I have reviewed a number of econometric approaches to the analysis of market definition and unilateral effects. I have suggested a number of approaches to the analysis of market definition, some of which emphasize the modeling and estimation of the structure of demand and others that represent short-cuts that can be applied when there are not sufficient data to estimate a complete demand system. With respect to the use of critical-loss analysis in defining relevant markets, the methodology is generally well understood, but the debate about its value continues to this day.

I have also discussed two compelling approaches to the analysis of unilateral effects – merger simulation and difference-in-differences analysis. I consider each of these methodologies to be of value. I am convinced that merger simulation methods are and will be of substantial value, and I expect that value to grow along with the debate as to which particular methods are most appropriate (relatively general demand structures requiring very substantial datasets versus simpler demand structures necessitating less substantial datasets). Finally, difference-in-differences analysis is a technique that is widely used in economics and whose applicability to antitrust analysis (with refinements) will also grow.

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