Portfolio Media. Inc. | 111 West 19th Street, 5th floor | New York, NY 10011 | www.law360.com
Phone: +1 646 783 7100 | Fax: +1 646 783 7161 | customerservice@law360.com

Estimating Antitrust Impact, Damages Via Natural Experiments

By **James Nieberding** (January 21, 2020, 6:03 PM EST)

James Nieberding

Economists generally cannot conduct randomized controlled experiments — like those done to test the efficacy of a new drug — to analyze the effects of a given event on market outcomes. They can, however, observe and study the effects of natural experiments, such as unexpected plant outages, natural disasters, the entry/exit of key competitors or a change in the economic/regulatory environment.

A 2018 **article** in Law360 provided an overview of how such natural experiments might be used to estimate economic damages in a difference-in-differences framework (though this technique was never specifically mentioned).[1]

This article provides a more detailed discussion of the DiD methodology and how it can be used to estimate impact or damages in a variety of situations based on an event that constitutes a natural experiment.

The DiD Methodology

Although implementation of DiD models vary in complexity, the idea is straightforward. Identify an event of interest, an outcome thought to be affected by the event and two groups — one group whose outcome is believed to be influenced by the event (the treatment) and another group whose outcome is not (the control).

Then take the difference in the outcome between these two groups before the event (which serves as the baseline) and again after it has occurred. The DiD effect is estimated as the difference-in-differences of these two metrics, as illustrated below.

As in a randomized controlled experiment, the DiD approach needs the control be highly similar to the treatment. This allows the control to be used as a benchmark against which to measure any effect of the event on the treatment.

For example, consider an economic application that investigates how a market outcome (e.g., prices, sales, market share) has responded to a claimed wrongful act. A valid control should be similar to the treatment in that supply, demand and other market factors affected each group in substantially the same way so that the only difference between the two groups is the challenged conduct.

Consider the case where the purpose of the analysis is to estimate a price premium due to an alleged false claim (e.g., a company mislabels a product as "all natural" when it shouldn't or falsely advertises a feature of dubious value in one of its products).

At its simplest, the DiD approach would compare prices of the items affected by the challenged conduct (the treatment products) to those of control products. These products essentially would be identical to the treatment products but-for the presence of the challenged conduct in that they would not contain the "all-natural" label or include the questionable product feature.

Suppose that T_B represents the average price of the treatment products before the challenged conduct; T_A represents its average price after the challenged conduct; C_B represents the average price of the control products before the challenged conduct; and C_A represents its average price after the challenged conduct. The DiD estimate (also called the treatment effect) is the difference-in-differences of these average prices, $(T_A - T_B) - (C_A - C_B)$, as seen in Table 1.

Table 1

	Pre Challenged Conduct	Post Challenged Conduct	Post v. Pre Difference
Treatment	T_B	T_A	$T_A - T_B$
Control	C_B	C_A	$C_A - C_B$
(Difference)	$(T_B - C_B)$	$(T_A - C_A)$	$\boldsymbol{(T_A - T_B) - (C_A - C_B)}$ *DiD Estimate*

The change in average price for the control before and after the challenged conduct provides a measure of the effect of the economic factors (e.g., supply, demand and other market forces) that are assumed to have similarly affected the treatment. This accounts for any market influences on treatment prices unrelated to the challenged conduct. As a result, the price change in the control (i.e., $C_A - C_B$) can be subtracted from the price change in the treatment (i.e., $T_A - T_B$) to assess the price effect of the challenged conduct.

Properly implemented, the DiD estimate may be interpreted as an estimate of the effect of the challenged conduct on the average price of the treatment products.[2] In this price-premium example, one can conclude that the challenged conduct is associated with an increase in the average price for the treatment products if the DiD estimate is statistically greater than zero.[3]

In identifying valid control products, it is important that these are affected by the same market forces that also affect the treatment products (other than the challenged conduct).[4] Doing so ensures that, by construction, the DiD analysis (implicitly) controls for the effects of these market forces on the price of the treatment products that would have occurred absent the claimed wrongful act. As a result, specific data on relevant supply, demand or other market factors that affected the pricing of the products under study is not required.

A DiD estimate typically is obtained using regression analysis which reports the standard error and significance level associated with it. In this example, under the assumption that the same factors affected the control and treatment prices, the effect of the challenged conduct can be estimated using only price data.[5]

A standard DiD regression model would then be specified as follows:

$$P_{it} = \hat{\beta}_0 + \hat{\beta}_1 treatment_{it} + \hat{\beta}_2 after_t + \hat{\beta}_3 (treatment_{it} * after_t)$$

P_{it} represents the price at time t in group i (where i denotes if the product is in the control or treatment); $treatment_{it}$ = 1 if observation i at time t is a treatment price (and 0 if not); and $after_t$ = 1 if the price occurs after the start of the challenged conduct (and 0 if before). The betas represent the estimated regression coefficients. The focus of the DiD model is the regression coefficient β_3 because it corresponds to the DiD estimate in Table 1. This can be seen in Table 2 by substituting in 0 or 1 as appropriate in the regression equation.

The DiD estimate in Table 2 is the difference of the post- versus predifference metrics, or ($\beta_2 + \beta_3$) - (β_2) = β_3. If β_3 is not statistically different from zero, the DiD regression model would indicated no significant change in treatment prices relative to control prices after the challenged conduct.

However, if β_3 were positive and statistically significant, this would offer empirical support (and quantification) for the claim of an increase in the average price of the treatment products (relative to control products) subsequent to the challenged conduct.[6]

Table 2

Treatment Prices (Post):	$P_{it} = \hat{\beta}_0 + \hat{\beta}_1(1) + \hat{\beta}_2(1) + \hat{\beta}_3(1)$	=	$\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$
Treatment Prices (Pre):	$P_{it} = \hat{\beta}_0 + \hat{\beta}_1(1) + \hat{\beta}_2(0) + \hat{\beta}_3(0)$	=	$\hat{\beta}_0 + \hat{\beta}_1$
	Post v. Pre Difference	=	$\hat{\beta}_2 + \hat{\beta}_3$
Control Prices (Post):	$P_{it} = \hat{\beta}_0 + \hat{\beta}_1(0) + \hat{\beta}_2(1) + \hat{\beta}_3(0)$	=	$\hat{\beta}_0 + \hat{\beta}_2$
Control Prices (Pre):	$P_{it} = \hat{\beta}_0 + \hat{\beta}_1(0) + \hat{\beta}_2(0) + \hat{\beta}_3(0)$	=	$\hat{\beta}_0$
	Post v. Pre Difference	=	$\hat{\beta}_2$

Applications of the DiD Methodology

The DiD model is a popular empirical tool used in economics, public policy, labor market studies, regulatory analysis and health care policy to compare outcomes between treatment and control groups.[7] It also is used to assess liability and damages in litigation matters and in a variety of nonlitigation settings.

Though applied in various situations and under different circumstances, all DiD models share the same basic statistical setup. That is, using the DiD approach to gauge the impact of an occurrence that constitutes a natural experiment, a comparison of outcomes is done for a treatment affected by the event to that of a control that did not experience the event but is otherwise similar to the treatment.

A variety of empirical economic applications use the DiD methodology. One relates to retrospective merger analysis that estimates the price (or market share) effects of consummated mergers.[8] In this use, the control would be products or geographic areas that were unaffected by the merger but otherwise similar to those products or geographic areas influenced by it.

The potential effects of prospective mergers likewise can be studied using the DiD approach based on natural experiments. As stated by U.S. antitrust agencies:

> The Agencies look for historical events, or "natural experiments," that are informative regarding the competitive effects of the merger. ... [I]f the merging firms compete in some locales but not others, comparisons of prices charged in regions where they do and do not compete may be informative regarding post-merger prices.[9]

For example, suppose a DiD analysis finds that an unexpected capacity or output reduction led to a sustained price increase in some region prior to a proposed merger. This could be used as evidence that a similar price increase might occur if a proposed merger in that same region were shown to have the incentive and ability to similarly reduce capacity or output.

A DiD model also could study the price effect of competitive entry with the treatment area being where the entry occurred and the control area being a similar region unaffected by the entry. If it were shown that the entry of a competitor significantly decreased prices, this would lend support the notion that the loss of an independent competitor post-merger in that same region might lead to higher prices.

Other uses of the DiD method relate to antitrust impact and damages and are regularly seen in a variety of litigation settings. For example, Forrest Mccluer and Martha Star present a DiD model to quantify antitrust damages in a health care matter due to an illegal market allocation scheme.[10]

Kai Hüschelrath, Kathrin Müller and Tobias Veith use publicly available data from a German cement cartel to analyze — in a DiD framework — the change in price for a cartelized market compared to the change in price in a noncartelized, benchmark market.[11] Ulrich Laitenberger and Florian Smuda estimate the damages suffered by German consumers due to a detergent cartel that was active between 2002 and 2005 in eight European countries using a DiD model.[12]

Ricard Gil (et. al.) use a DiD estimate for movie outcomes (prices, attendance) to investigate whether vertical integration facilitates market foreclosure in Chinese media markets.[13]

In In Re Evanston Northwestern Corporation Antitrust Litigation,[14] the U.S. District Court for the Northern District of Illinois accepted the proposed DiD methodology to determine antitrust impact in granting class certification. A second notice of filing public version of the expert report in The Shane Group Inc. v. Blue Cross Blue Shield of Michigan[15] details the application of a DiD regression model which estimated the change in average hospital reimbursement rates before and after implementation of most-favored nations clauses.

In a petition for a writ of certiorari to the U.S. Supreme Court in U.S. Department of Commerce v. State of New York,[16] an empirical study done by the U.S. Census Bureau in 2018 is presented, which contains a DiD analysis investigating discrepancies between survey-collected citizenship data and administrative records on citizenship from the Social Security Administration.

A 2019 study used a DiD model to investigate the effect on salaries of "no-poach" agreements that recently were the focus of a U.S. Department of Justice investigation as well as civil litigation.[17]

Another 2019 study used a DiD model to analyze the impact of the Supreme Court's decision against mandatory expansion of Medicaid eligibility (under the Patient Protection and Affordable Care Act), concluding that counties in states that expanded Medicaid had a significantly smaller increase in rates of cardiovascular mortality for middle-aged adults after expansion than states that did not expand Medicaid.[18]

Validity of the DiD Approach

Although intuitive, the DiD estimate requires some necessary conditions for its reliable use in estimating damages.[19] A guiding principle regarding the validity of the DiD approach is that to be a suitable benchmark, the control needs to be identical in all significant respects to the treatment except for exposure to the event being study.

This "common shock" assumption requires that the control and treatment respond to changes in the same factors (e.g., cost, demand and supply) in very similar ways and that the treatment behaves like the control in the absence of the event. If significant differences are found to exist between the control and treatment, the analysis needs to include this information.

Any factor that affects the outcome of interest and is correlated with the metric whose effect is being measured should also be included. Though some of these factors may be difficult to incorporate into the DiD model (e.g., the necessary data are not available), failure to do so subjects the DiD estimate to criticisms related to omitted variable bias.

A DiD model also relies on the assumption that in the absence of the event under study, the treatment and control would have had the same trends in average outcome. This "parallel trends" assumption is a required condition for the validity of the DiD estimate.[20]

That is, if trends in outcomes experienced by the control and treatment before the event are similar, it is reasonable to assume that this relationship would have continued absent the event. If this assumption is satisfied, then the trend in outcome of the control after the event can serve as a valid estimate of the counterfactual trend for the treatment.

In sum, a valid use of the DiD approach to estimate damages requires that all necessary logical and methodological conditions are met.

James F. Nieberding, Ph.D., is the principal and founder of North Coast Economics LLC.

[1] "How Natural Experiments Can Help In Estimating Damages," Law360, February 15, 2018.

[2] In this way, a DiD model does (implicitly) address causation by comparing changes in averages prices for the Treatment and Control products before and after the event. If the Control products are virtually identical in all significant respects to the Treatment products, then any change in price between them pre- and post-event reasonably may be interpreted as an estimate of the effect of the event.

[3] Statistical software will report the significance of the DiD estimate.

[4] The Treatment and Control products must also be sufficiently distinct from each other so that the challenged conduct would not have impacted the Control products.

[5] The DiD regression model can be augmented with additional explanatory variables to account for different economic and other market factors on prices between the Control and Treatment products should they exist. This could provide a further ability to isolate the effect of the challenged conduct on the average price of the Treatment products.

[6] The coefficient $\beta 1$ represents the "baseline" difference in average price that existed between the Treatment and Control products prior to the challenged conduct (i.e., (TB – CB) in Table 1). The coefficient $\beta 2$ is the change in average price pre- v. post-challenged conduct for the Control products (i.e., (CA – CB) in Table 1).

[7] Citations to the wide-ranging applications of the DiD methodology are vast. For a good example, see, e.g., Andrew M. Ryan, James F. Burgess Jr., and Justin B. Dimick (2015), "Why We Should Not Be Indifferent to Specification Choices for Difference-in-Differences," Health Services Research 50(4), pp. 1211-1235.

[8] See. e.g., Joseph Farrell, Paul A. Pautler and Michael G. Vita (2009), "Economics at the FTC: Retrospective Merger Analysis with a Focus on Hospitals," Review of Industrial Organization, Vol. 35, No. 4 (Special Issue: Antitrust and Regulatory Review), pp. 369-385; and, Graeme Hunter, Gregory K. Leonard and G. Steven Olley (2008), "Merger Retrospective Studies: A Review," Antitrust, Vol. 23, No. 1, pp. 34-41.

[9] Horizontal Merger Guidelines (https://www.justice.gov/atr/horizontal-merger-guidelines-08192010, at 2.1.2).

[10] R. Forrest Mccluer and Martha A. Star (2013), "Using Difference in Differences to Estimate Damages in Healthcare Antitrust: A Case Study of Marshfield Clinic," Int. J. of the Economics of Business, Vol. 20, No. 3, pp. 447–469.

[11] Kai Hüschelrath, Kathrin Müller and Tobias Veith, "Concrete Shoes for Competition: The Effect of the German Cement Cartel on Market Price," Journal of Competition Law and Economics 9(1), pp. 97-123.

[12] Ulrich Laitenberger and Florian Smuda, "Estimating Consumer Damages in Cartel Cases," Journal of Competition Law and Economics, 11(4) (December 2015), pp. 955-974.

[13] Ricard Gil, Chun-Yu Ho, Li Xu and Yaying Zhou (2019), "Vertical Integration and Market Foreclosure in Media Markets: Evidence from the Chinese Motion Picture Industry," Working Paper,

International Industrial Organization Conference (Boston).

[14] U.S. Dist. Court For N. Dist. Of Illinois, E. Div. (Memorandum Opinion and Order, December 10, 2013).

[15] U.S. Dist. Court For E. Dist. Of Michigan, S. Div., (April 20, 2018).

[16] (filed Jan. 25, 2019; Certiorari granted Feb. 15, 2019).

[17] Gibson, Matthew (2019). “Employer Market Power in Silicon Valley.” Working Paper, Department of Economics, Williams College.

[18] Khatana et. al. (2019), “Association of Medicaid Expansion With Cardiovascular Mortality,” JAMA Cardiology 4(7), pp. 671-679.

[19] See, e.g., Frank P. Maier-Rigaudi and Slobodan Sudaric, “The Difference-in-Differences Approach to Cartel Damages,” CPI Antitrust Chronicle, June 2019.

[20] For alternate methods to the DiD approach where the parallel trends assumption is untenable, see Stephen O’Neill, N. Kreif, R. Grieve, M. Sutton, and J. S. Sekhon (2016), “Estimating Causal Effects: Considering Three Alternatives to Difference-in-Differences Estimation.” Health Services and Outcomes Research Methodology 16, pp. 1–21.