

EVOLVING OR RUNNING IN PLACE? EMPIRICAL APPROACHES TO “COMMON IMPACT” IN ANTITRUST CLASS ACTIONS

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I. INTRODUCTION

1. In class action litigation, a court’s decision as to whether a particular class should be certified turns, in part, on the question of predominance.¹ In antitrust class actions in particular, the predominance assessment relies heavily on economic analysis. Plaintiffs’ expert economists offer opinions on whether evidence common to the proposed class can establish antitrust impact—i.e., paying actual prices higher than in a “but-for” world absent the alleged conspiracy—to all (or nearly all) members of that class. Defendants’ expert economists are asked to assess those opinions.
2. Plaintiffs’ expert economists generally rely on three broad categories of economic evidence to assess issues of predominance. The first category involves analysis of what is referred to as “common industry characteristics.” Plaintiffs’ expert may describe certain characteristics of the industry at issue—e.g., a small number of competitors, high barriers to entry, and absence of substitutable products—and opine that economic theory predicts a higher likelihood of classwide impact in industries where such characteristics are present.² This type of analysis is generally not definitive because it offers no objective criteria to test the proposition of classwide impact. There is no test or bright line rule, for example, dictating how concentrated the industry at issue should be to establish that the alleged conduct harmed the entire proposed class.
3. A second type of economic evidence often offered by plaintiffs’ expert economists as part of the predominance inquiry involves “pooled” regression models that aim to statistically identify overcharges (i.e., price elevations resulting from the alleged conduct). These models are referred to as “pooled” because they combine sales data across proposed class members and estimate a single average overcharge. The shortcomings of pooled regression models for the predominance inquiry have

¹ FED. R. CIV. P. 23(b)(3) requires that “questions of law or fact common to class members *predominate* over any questions affecting only individual members....” (emphasis added).

² See, e.g., Memorandum L. in Support of Direct Purchaser Plaintiffs’ Motion for Class Certification at 50–51, *In Re: Domestic Drywall Antitrust Litig.*, No. 2:13-md-2437-MMB (Aug. 3, 2016) [hereinafter *Drywall Class Certification Motion*] (Plaintiffs’ expert “establish[ed] market factors that made it far more likely that the Cartel would be successful in widely imposing conspiratorial prices across the Class.... Such factors include: Market concentration and Co-Conspirators’ domination of the Drywall market, ... Lack of economic substitutes, ... High barriers to entry.”); Direct Purchaser Plaintiffs’ Motion for Class Certification, & Memorandum L. In Support at 13, *In re Capacitors Antitrust Litig.*, No. 3:14-cv-03264-JD (June 15, 2017) (Plaintiffs’ expert “described various characteristics of the capacitor industry that would cause economists to deem it susceptible to collusion, ... including Defendants’ market power in a concentrated industry, ... high barriers to entry, ... and inelastic and declining demand.”); Memorandum L. In Support of Direct Purchaser Plaintiffs’ Motion For Class Certification at 4–5, *In Re: Interior Molded Doors Antitrust Litig.*, No. 3:18-cv-00718-JAG (Mar. 9, 2021) [hereinafter *IMD Class Certification Motion*] (“Class-wide evidence shows that the IMD market possesses characteristics that facilitate (1) collusion, and (2) widespread harm on all Class members. These include: Dominant market power, [...] Significant barriers to entry exist, [...] Demand for IMDs is inelastic as there are no reasonable economic substitutes, [...] IMDs are commodities....”).

been extensively discussed in the economic literature.³ Pooled overcharge models are generally referred to as “representative” evidence—i.e., evidence meant to “represent” the experiences of class members through an average, rather than directly assess each *individual* class member’s experience (which may or may not be different than the average).⁴

4. Given the limitations of the pooled overcharge model for establishing injury to all (or nearly all) members of a given proposed class, plaintiffs’ expert economists often offer a third type of economic evidence, which is referred to as analysis of “common impact.” This type of analysis—which has been implemented in the form of several different empirical methodologies—seeks to supplement the pooled overcharge models and fill the analytical gap with respect to assessing injury on a classwide basis.⁵ However, any such “common impact” techniques should be evaluated rigorously, as they often go no further than the pooled regressions they intend to supplement in terms of addressing issues of masking individualized differences and sweeping in uninjured class members.
5. As the economic analysis of antitrust class certification continues to become more complex and data intensive, “courts have continued to scrutinize average-pricing models, the propriety of which depends not only on a proposed class’s theory of liability but on the degree to which they account for variation of injury between class members.”⁶ A variety of economic methodologies have emerged with the supposed intent of assisting courts in this scrutiny. Some—called “price structure” methodologies—seek to *supplement* the pooled overcharge model and do not, in and of themselves, rely on that type of model. Others—called “but-for price” methodologies—seek to *extend* the results from the pooled overcharge model. But are these techniques advancing the ball in terms of helping courts deliberate on the question of predominance? Or are they simply repackaging the same issues under the guise of supposedly increased rigor and precision? Given the increasingly technical nature of these “common impact” methodologies, this paper aims to arm practitioners and courts with a better understanding of how they work and where they may (or may not) add value.

3 See e.g., Laila Haider et al., *Turning Daubert on its Head: Efforts to Banish Hypothesis Testing in Antitrust Class Actions*, 30 *Antitrust* 53 (2016) [hereinafter Haider et al.]; ABA ANTITRUST L. SECTION, *ECONOMETRICS: LEGAL, PRACTICAL, AND TECHNICAL ISSUES* 357 (Lawrence Wu et al. eds., 2d ed. 2014) [hereinafter ABA *ECONOMETRICS*]; John H. Johnson & Gregory K. Leonard, *Economics and the Rigorous Analysis of Class Certification in Antitrust Cases*, 3 *J. COMPETITION L. & ECON.* 341 (2007); John H. Johnson & Gregory K. Leonard, *Rigorous Analysis of Class Certification Comes of Age*, 77 *ANTITRUST L.J.* 569 (2011); Bret M. Dickey & Daniel L. Rubinfeld, *Antitrust Class Certification: Towards an Economic Framework*, 66 *NYU ANN. SURV. AM. L.* 459 (2011); Pierre Cremieux et al., *Proof of Common Impact in Antitrust Litigation: The Value of Regression Analysis*, 17 *GEO. MASON L. REV.* 939 (2010); Michelle M. Burtis & Darwin V. Neher, *Correlation and Regression Analysis in Antitrust Class Certification*, 77 *ANTITRUST L.J.* 495 (2011) [hereinafter Burtis & Neher (2011)].

4 By way of a simple example with only two proposed class members, if one was overcharged by 20 percent while the other was not overcharged at all, a pooled overcharge model may find an average 10 percent overcharge across the two class members. Such an overcharge could only represent the average experience of the entire class, not each individual member’s actual experience and potential injury.

5 See, e.g., *Drywall Class Certification Motion*, *supra* note 2, at 3–4 (“DPPs’ impact analysis proceeds in two steps: (i) demonstrating that Drywall prices were artificially inflated generally due to the Cartel; and (ii) showing that a price structure exists, making it highly likely that Class members broadly paid those artificially inflated prices.”).

6 William F. Cavanaugh et al., *Trends in Class Certification*, *US CTS. ANN. REV.* (2023), globalcompetitionreview.com/review/us-courts-annual-review/2023/article/trends-in-class-certification.

II. “PRICE STRUCTURE” AS A PROPOSED METHODOLOGY FOR ASSESSING COMMON IMPACT

6. The “price structure” methodology is one approach that has been offered as a supplement to the pooled overcharge regression model. This methodology seeks to establish that prices in the relevant industry, while not necessarily the same across all proposed class members, nonetheless follow a common and predictable “structure,” i.e., they tend to move together over time in response to economic forces.⁷ This approach is typically used to argue that because of an existing “price structure,” it would be unlikely that many (or potentially any) proposed class members could avoid the average overcharge estimated by the pooled regression model.⁸ Put differently, even if the average overcharge does not separately establish impact for Customer A and Customer B, the price structure analysis is meant to establish that the two customers’ prices follow similar patterns, so that an average overcharge is adequate to represent the experiences of both. Likewise, a finding of “price structure” also purports to show that common pricing factors predominate over individualized ones.
7. Attempts to analyze predominance issues in antitrust class actions using a “price structure” framework are not new. Nor are the issues raised by this framework with respect to whether it is actually showing class-wide impact, inferring it, or simply studying an issue that does not bear on the question of predominance at all. For example, in 2007, Johnson and Leonard explained that this is “not a standard concept found in the economic literature” and discussed contemporaneous approaches which relied on visual inspection of pricing graphs as lacking scientific rigor.⁹ In 2011, Burtis and Neher discussed a variety of antitrust class actions where plaintiffs offered arguments based on “price structure” theories, as well as correlation analyses offered in support of those theories.¹⁰

⁷ The exact definition of “price structure” varies across experts and cases, but the notion of prices “tending to move together over time in response to economic forces” generally captures this concept. *See, e.g.*, ABA Econometrics, *supra* note 3, at 354 (“While the term ‘price structure’ often is not precisely defined, it usually refers to a situation where prices stay in fixed relation to each other over time. Furthermore, the concept of a pricing structure is not well-established in the economics literature or profession.”); Drywall Class Certification Motion, *supra* note 2, at 49 (“prices to customers and across sellers tend to move together over time, and that a common factor affecting prices (such as Cartel behavior) will be experienced across the market.”); IMD Class Certification Motion, *supra* note 2, at 31 (“the prices customers paid, regardless of the seller, tended to move together over time, and that a common factor affecting prices (such as conspiratorial behavior) will be experienced across the market.”).

⁸ Economic experts relying on “price structure” arguments typically contend that it leads to the inference that substantial individualized differences across class members are unlikely and that representative evidence such as average overcharges indeed represents each class member’s individual experience. To continue with the simple example in footnote 4, the expert would opine that a finding of “price structure” would imply the average 10 percent overcharge would be representative of both class members, and that it would be unlikely for one of the class members to have avoided impact from the alleged conduct.

⁹ John H. Johnson & Gregory K. Leonard, *In the Eye of the Beholder: Price Structure as Junk Science in Antitrust Class Certification Proceedings*, 22 ANTITRUST 108, 110 (2008).

¹⁰ Burtis & Neher, *supra* note 3, n.2 (citing *In re Urethane Antitrust Litig.*, 237 F.R.D. 440 (D. Kan. 2006); *In re Rubber Chems. Antitrust Litig.*, 232 F.R.D. 346, 353 (N.D. Cal. 2005); *Winoff Indus. v. Stone Container Co.* (*In re Linerboard Antitrust Litig.*), 305 F.3d 145, 153 (3d Cir. 2002); *In re Dynamic Random Access Memory (DRAM) Antitrust Litig.*, No. M 02-1486 PJH (N.D. Cal. June 5, 2006), *aff’d*, 546 F.3d 981 (9th Cir. 2008); *In re Static Random Access (SRAM) Antitrust Lit.*, No. C 07-01819 CW (N.D. Cal. Sept. 29, 2008); *In re Pressure Sensitive*

8. The concept of “price structure” continues to be offered as a prong of the predominance analysis.¹¹ While “price structure” analyses have evolved from visual inspections of graphs to more sophisticated statistical and econometric techniques, this evolution has not resolved the fundamental maladaptation of the “price structure” concept for assessing impact across members of a given proposed class. Despite some evolution over the last decade in how they are implemented technically, “price structure” methodologies have little to add to the analysis of class-wide impact because they offer neither (i) an objective definition of what constitutes such a “structure” nor (ii) any direct relationship between any such “structure” and whether none, some, or all members of a given class suffered impact from an alleged course of antitrust misconduct.
9. One statistical methodology that has been used by plaintiffs’ economic experts to purportedly assess “price structure” is called hedonic price regression. These types of regression models are based on the assumption that prices for products at issue are determined by their discrete characteristics, and they attempt to decompose prices into the corresponding values for each standalone characteristic.¹² An example of these models’ application is estimating real estate prices based on a given property’s characteristics such as the numbers of bedrooms and bathrooms, square footage, and lot size. In such an application, the hedonic price regression models would seek to estimate the effect of an incremental change in one of the characteristics—e.g., an additional bedroom, bathroom, or square foot—on a property’s price.
10. In recent years, hedonic regression models have been incorporated into analysis of common impact issues in the antitrust class certification context.¹³ The concept these models purport to study is how much of the variation in prices for the products at issue can be explained by their characteristics, rather than differences across the proposed class members that purchased them. For example, if a large share of price variation could be explained by product characteristics (and thus, only a small share of the variation would relate to class member-specific factors), then there must be an overarching “structure” governing prices. Put differently, if it is simply the case that some class members purchased a more expensive

Labelstock Antitrust Litig., No. 3:03-MDL-1556 (M.D. Pa. Nov. 19, 2007); *In re Graphics Processing Units Antitrust Litig.*, 253 F.R.D. 478, 493 (N.D. Cal. 2008); *In re Catfish Antitrust Litig.*, 826 F. Supp. 1019, 1041 (N.D. Miss. 1993).

- 11 See, e.g., Drywall Class Certification Motion, *supra* note 2, at 49 (“The Presence of a Price Structure Confirms Common Impact.”); IMD Class Certification Motion, *supra* note 2, § IV.B.1.b.ii.a (“A Pricing Structure Exists in the IMD Market Such That Prices Responded Similarly to Coordinated Pricing Activity.”)
- 12 More specifically, the assumption underlying hedonic price regression is that consumers separately value the characteristics of the products rather than the products themselves. As a result, and under certain assumptions, different consumer valuations result in prices for the relevant products that are based on each product’s characteristics. (See, e.g., Frederick V. Waugh, *Quality Factors Influencing Vegetable Prices*, 10 J. FARM ECON. 185 (1928); Kelvin J. Lancaster, *A New Approach to Consumer Theory*, 74 J. POL. ECON. 132 (1966); Sherwin Rosen, *Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition*, 82 J. POL. ECON. 34 (1974); Jae Bong Chang et al., *The Price of Happy Hens: A Hedonic Analysis of Retail Egg Prices*, 35 J. AGRIC. & RES. ECON. 406 (2010); Jeffrey Anstine, *Organic and All-Natural: Do Consumers Know the Difference?*, 26 J. APPLIED ECON. & POL’Y 15 (2007); Biing-Hwan Lin et al., *Organic Premiums of Fresh Produce*, 23 RENEWABLE AGRIC. & FOOD SYS. 208 (2008); Laura O. Taylor, *Hedonics*, in A PRIMER ON NONMARKET VALUATION 331 (Patricia A. Champ et al. eds., 2003).
- 13 See, e.g., IMD Class Certification Motion, *supra* note 2, at 32 (Plaintiffs’ expert “performed regressions that examined each Defendant’s sales in each month of the Class Period The results of this regression analysis show that ‘85 to 91 percent of all variation in the price of IMDs is explained by the common characteristics, suggesting that common factors explain nearly all variation in prices at any given point in time.’”).

version of the product and others purchased a cheaper version—but all prices are subject to a “structure”—then (the argument goes) there are no individualized class member-specific issues beyond the need to account for what any individual purchased.

11. In general, the “share of price variation explained by products characteristics” has been assessed using a statistical measure called the “R-squared.”¹⁴ However, R-squared analysis—like the correlation analysis described in the price structure literature from a decade ago—is subject to issues that ultimately render it of little value for assessing the economic questions of common impact. First, to the extent that “price structure” relates to the co-movement of prices *across purchasers* and *over time*, hedonic price regressions appear to be a misguided instrument to study it. Because they only seek to decompose prices into underlying characteristics, hedonic price regressions specifically *do not* study price movements across purchasers or over time. Nor do they attempt to assess whether any price movements across purchasers or over time were common. The R-squared statistic of hedonic price regressions therefore bears no relationship to the “price structure” concept as it has been defined in the class certification context.
12. Moreover, like the correlation analyses described in the price structure literature from a decade ago, there are no objective, established, or widely accepted criteria to determine what threshold levels of R-squared constitute a substantial enough share of variation such that it is indicative of a “price structure.” The R-squared statistic calculated from a given regression may be equally “high” irrespective of whether all, some, or even none of the proposed class has been impacted. In fact, the mathematical and statistical properties of the R-squared in a hedonic price regression make it a particularly paradoxical metric of “price structure” because it tends to mechanically increase—purportedly implying *more* “price structure”—as the number and variety of products included in the model increases. The notion that increased diversity in the set of products at issue leads to a *higher* degree of “price structure”—described in the literature as the “diversity paradox”¹⁵—does not make sense as a matter of economics and suggests that a “high” R-squared value from the hedonic price regressions cannot be interpreted as evidence of “common impact.”

¹⁴ The R-squared statistic takes values between 0 and 1 and measures the share of variance in prices (the “dependent” variable in the regression) that can be explained by product characteristics (the “independent” variables in the regression). As widely noted in the econometrics literature, the R-squared is generally not a meaningful measure of regression reliability. (See, e.g., DAMODAR N. GUJARATI & DAWN C. PORTER, *BASIC ECONOMETRICS* 206 (5th ed. 2004) [hereinafter GUJARATI] (“[A] warning is in order: Sometimes researchers play the game of maximizing R², that is, choosing the model that gives the highest R². But this may be dangerous, for in regression analysis our objective is not to obtain a high R² per se but rather to obtain dependable estimates of the true population regression coefficients and draw statistical inferences about them [... A] high R² is not evidence in favor of the model and a low R² is not evidence against it.”). See, also, Rubinfeld, 2011, p. 345; Wooldridge 5th ed., pp. 39, 200; ROBERT S. PINDYCK & DANIEL L. RUBINFELD, *MICROECONOMICS* 704 (8th ed. 2009); *ECONOMETRICS* 100 (ABA 2014).

¹⁵ Burtis and Neher (2011) call this property of the R-squared statistic the “diversity paradox” and explain that “the more diverse the products and consumers in a putative class, the higher the R-squared in the regression model that attempts to ‘control’ for this diversity.” (Burtis & Neher, *supra* note 3, at 521.)

III. “BUT-FOR PRICES” PREDICTED BY POOLED REGRESSIONS AS PROPOSED METHODOLOGY FOR ASSESSING COMMON IMPACT

13. The hedonic “price structure” methodologies discussed above seek to *supplement* the pooled overcharge model and do not, in and of themselves, rely on that type of model. However, in several antitrust class actions in recent years,¹⁶ plaintiffs’ economic experts have also offered another type of methodology, which seeks to *extend* the pooled overcharge model. The basic premise of this “extension” is that it calculates “predicted but-for prices” using the pooled overcharge model and then compares those predictions to actual prices paid, purporting to evaluate antitrust impact for every transaction—and thus determine whether each class member suffered injury.
14. This extension of the pooled overcharge model tends to conflate the generally uncontroversial premise that antitrust injury should be evaluated by comparing actual and reliably estimated but-for prices,¹⁷ and the specific shortcoming of pooled models’ usefulness for the predominance inquiry. As discussed above, the well-documented issue with pooled overcharge regression models in the context of class certification analysis is that they purport to “represent” the experiences of class members through an average but have no ability to directly assess each *individual* class member’s experience—i.e., whether any individual’s experience differs from the average. Applying the single average overcharge generated by a pooled model to each class members’ purchases does not somehow “individualize” the pooled model—i.e., it does not allow the model to directly assess each individual class member’s experience. Rather, it provides the appearance that the pooled model is capable of individualized analysis of antitrust impact while simply repackaging the single average overcharge.
15. Consider a stylized version of the standard pooled overcharge regression, summarized in equation [1]:
$$\text{Actual Price}_i = \beta_0 + \beta_1(\text{Supply Factors}) + \beta_2(\text{Demand Factors}) + \beta_3(\text{Affected Transaction}) + \varepsilon_i \quad (1)$$
This model framework seeks to explain actual prices proposed class members paid (as represented on the left side of the equation). On the right side of the equation, the model includes factors that economic theory suggests explain those prices. For

¹⁶ See, e.g., Memorandum re: Direct Purchaser Plaintiffs’ Motion for Class Certification at 49 & 52, *In Re: Domestic Drywall Antitrust Litig.*, No. 2:13-md-2437-MMB (Aug. 23, 2017) (Plaintiffs’ expert “concludes from his model that because the overcharge indicator variables are positive and statistically significant, this shows that prices were artificially inflated by the alleged cartel” [and] “then conducts two additional empirical analyses to show that all or virtually all drywall purchasers were affected by the conspiratorial price increase....”); IMD Class Certification Motion, *supra* note 2, at 33 (Plaintiffs’ expert “performed another analysis—one built on the regression model used to find that the Conspiracy artificially inflated prices during the Class Period—that used a ‘predicted pricing approach’ to estimate Class member-specific overcharges.”); *In re Capacitors Antitrust Litig.*, Transcript of Proceeding, September 17, 2019, at 6 (Plaintiffs’ expert describing an “econometric methodology [that] is applied [...] in two steps. The first step is testing a hypothesis of whether or not prices were elevated above what would be predicted by normal market factors. [...] And the second step – once the model is estimated – is to drill down to the individual transaction and customer level with that model.”)

¹⁷ ABA SECTION OF ANTITRUST LAW, PROVING ANTITRUST DAMAGES: LEGAL AND ECONOMIC ISSUES chs. 8.A, 9.C.2. (3d ed. 2017) [hereinafter PROVING ANTITRUST DAMAGES] (“This analysis starts with the translation of the legal theory of harm into economic effects, which requires a comparison of the economic situation of the plaintiff with (the actual world) and without (the but-for world) the anticompetitive conduct.”)

example, if the cost of raw materials or labor needed to manufacture a product increases, the price of that product may increase to cover the additional cost. The coefficient β_1 on the right side of equation [1] represents the relationship between a change in cost (and any other relevant supply factors) and prices paid. Similarly, if demand for a product changes, economic theory would suggest that prices change as well. The coefficient β_2 on the right side of equation [1] represents the relationship between a change in demand and prices paid.

16. Any effects resulting from alleged anticompetitive behavior would be separate from the ordinary forces of supply and demand. In fact, “the economic model used must **isolate** the effect of the anticompetitive conduct”¹⁸ from the effects of these ordinary economic forces. The model in equation [1] includes a variable labeled “Affected Transaction,” which aims to capture any effects resulting from anticompetitive behavior. That is, this variable identifies transactions alleged to have been affected by anticompetitive behavior and the coefficient β_3 seeks to measure any elevation in the prices paid in those transactions that *cannot* be explained by ordinary economic forces.
17. Another relevant element of the model in equation [1] is the “prediction error” or “error term,” represented by ϵ_i . Prediction error is inherent to regression analysis—even in models that are properly specified¹⁹—because models are simplifications of real-life phenomena. There are several well-recognized sources of these errors. For example, many real-life phenomena are affected by a large number of factors, some of which may not lend themselves to adequate quantification for the purposes of inclusion in regression analysis. The error term may capture measurement error associated with the included explanatory variables when those variables cannot be precisely quantified. The error term can also be thought of as capturing the inherent randomness in human behavior, which may yield different outcomes even in identical circumstances.²⁰ In the context of the price model in equation [1], the error term ϵ_i captures the variation in prices that “simply cannot be explained by the model.”²¹ It does not reflect any effect of the alleged anticompetitive conduct.²²
18. When the price model in equation [1] is applied to a set of transaction-level sales data points, it seeks to find “the best-fitting straight line through [that] set of points.”²³ In practice, this means the regression seeks to model actual prices paid based on ordinary economic factors as well as any potential effects from anticompetitive conduct. However, for the reasons described above—namely, that models are simplifications of real-life phenomena—the actual prices *modeled* by the regression are not necessarily the same as the actual prices that proposed

18 *Id.* at ch. 4.C. (emphasis added)

19 For purposes of discussion here, assume the stylized model in equation [1] is properly specified. However, if the regression model is mis-specified, the resulting coefficient estimates may be biased and unreliable, which would affect the error terms as well. (*See, e.g., id.* at 163–64.)

20 *See e.g.*, PETER KENNEDY, A GUIDE TO ECONOMETRICS 3–4 (5th ed. 2008).

21 A. H. STUDENMUND, USING ECONOMETRICS: A PRACTICAL GUIDE 9 (6th ed. Pearson 2021) [hereinafter USING ECONOMETRICS].

22 *See, e.g.*, GUJARATI, *supra* note 14, at ch. 2.5 (“the disturbance term u_i is a surrogate for all those variables that are omitted from the model but that collectively affect Y.”)

23 DANIEL L. RUBINFELD, REFERENCE GUIDE ON MULTIPLE REGRESSION 335 (3d ed. 2011).

class members paid. The difference between *actual prices* and *modeled actual prices* is the model’s “prediction error.” As equation [2] shows, the error term ϵ_i is not part of the modeled actual price.²⁴

$$\begin{aligned} \text{Modeled Actual Price}_i = & \widehat{\beta}_0 + \widehat{\beta}_1(\text{Supply Factors}) \\ & + \widehat{\beta}_2(\text{Demand Factors}) \\ & + \widehat{\beta}_3(\text{Affected Transaction}) \end{aligned} \quad (2)$$

19. Each of the “betas” (also called “coefficients”) in equation [2] represents a numerical value produced by the regression model that represents the relationship between a particular economic factor and prices paid. For example, the coefficient $\widehat{\beta}_3$ would be a numerical value representing elevation in prices in transactions affected by the alleged anticompetitive conduct that cannot be explained by ordinary economic factors. If the model estimates that the alleged anticompetitive conduct elevated prices by approximately 10 percent, the model would produce a coefficient $\widehat{\beta}_3$ that would be approximately equal to 0.1. Importantly, the model in equation [2] is designed to estimate a single “pooled” overcharge across all transactions subject to the alleged conduct. Thus, a $\widehat{\beta}_3$ estimate approximately equal to 0.1 would represent an average 10 percent overcharge across all transactions included in the model and would not necessarily represent an overcharge of that size on all (or even any) individual transactions.²⁵

20. The above represents the type of “pooled” overcharge model that is often presented in antitrust class actions. The extensions of these pooled models as purportedly informing the issue of “classwide impact” proceed as follows. Based on the generally uncontroversial premise that antitrust injury should be evaluated by comparing actual and reliably estimated but-for prices, the economist proffering this approach calculates but-for prices “predicted” by the pooled model for each transaction. This calculation, represented in equation [3], removes the overcharge ($\widehat{\beta}_3$) from the prices modeled by the regression.

$$\begin{aligned} \text{Modeled But for Price}_i = & \widehat{\beta}_0 + \widehat{\beta}_1(\text{Supply Factors}) \\ & + \widehat{\beta}_2(\text{Demand Factors}) \end{aligned} \quad (3)$$

Once these but-for prices are calculated, the economist proffering this approach determines “impact” corresponding to each sales transaction by comparing the calculated but-for prices from equation [3] to the actual price paid. The comparison is shown in equation [4].

$$\text{Overcharge}_i = \text{Actual Price}_i - \text{Modeled But for Price}_i \quad (4)$$

Any transaction where the actual price is greater than the calculated but-for price is deemed in this type of analysis to have been impacted by the alleged conduct, and any proposed class member with at least one such transaction is deemed to have suffered antitrust injury as a result of the alleged anticompetitive conduct.

²⁴ Coefficients with a “hat” sign on top correspond to the estimated regression values of the true coefficients.

²⁵ Recall the simple example in footnote 4, where the average overcharge was 10 percent despite neither of the class members having individually paid that specific overcharge.

21. This seemingly straightforward approach for purportedly comparing actual and but-for prices for each individual transaction has two crucial elements. One is the single pooled overcharge coefficient this model estimates—represented by $\widehat{\beta}_3$ in equation [2]. The other is the transaction-specific error term—represented by ε_i in equation [1]. Mathematically, the transaction-level overcharge calculated through this approach for affected transactions is equivalent to:

$$\text{Overcharge}_i = \widehat{\beta}_3 + \widehat{\varepsilon}_i \quad (5)$$

Thus, the supposedly transaction-level overcharge calculated by this approach is the sum of (i) the single pooled overcharge (i.e., the 10 percent in the illustration above), and (ii) the portion of the price paid in a given transaction that “simply cannot be explained by the model.”²⁶ The only variation in these supposedly transaction-level overcharges results from the latter component—which captures the inherent randomness and not the effects of anticompetitive conduct. In other words, there is no transaction-level (or class member-level) estimate of the effects of anticompetitive conduct in this calculation.

22. Consider the following illustrative example of this issue, summarized in **Exhibit 1**:

- Five different proposed class members purchased the same product, each negotiating different prices which ranged from \$0.82 to \$1.15 (column [b] in the exhibit).
- Because the pooled overcharge regression model only estimates “common” supply and demand relationships, as well as a “common” overcharge (represented by $\widehat{\beta}_0$, $\widehat{\beta}_1$, $\widehat{\beta}_2$, and $\widehat{\beta}_3$ in equation [2]), it models uniform actual and but-for prices for all proposed class members. In this example, the regression predicts:
 - an actual price of \$1.00 for each customer (column [c] in the exhibit), meaning the “prediction errors” generated by the regression range from -\$0.18 (for Customer A) to \$0.15 (for Customer E) (column [d] in the exhibit).
 - a but-for price of \$0.90, meaning the estimated average overcharge is \$0.10, or 10 percent (columns [e] and [f] in the exhibit).²⁷

The “individual overcharges” that would be calculated by this methodology for each proposed class member are shown in column [g] of the exhibit.

²⁶ USING ECONOMETRICS, *supra* note 29, at 9.

²⁷ The overcharge represents the share of actual price that is attributable to the alleged conduct. Note that it is not necessary to the example that the modeled actual and but-for prices—which in this example are \$1.00 and \$0.90, respectively—be identical across customers. Even if they are not, the construction of the pooled overcharge model would estimate a single overcharge percentage across all customers.

Customer	Actual Price (Equation [1])	Predicted Actual Price (Equation [2])	Prediction Error (ϵ_i)	Predicted But- For Price (Equation [3])	Pooled Overcharge (β_3)	"Individual" Overcharge (Equation [4])
[a]	[b]	[c]	[d]=[b]-[c]	[e]	[f]=1-[e] / [c]	[g]=[d]+([c]-[e])
A	\$0.82	\$1.00	-\$0.18	\$0.90	10%	-\$0.08
B	\$0.96	\$1.00	-\$0.04	\$0.90	10%	\$0.06
C	\$0.99	\$1.00	-\$0.01	\$0.90	10%	\$0.09
D	\$1.08	\$1.00	\$0.08	\$0.90	10%	\$0.18
E	\$1.15	\$1.00	\$0.15	\$0.90	10%	\$0.25

EXHIBIT 1. ILLUSTRATIVE CALCULATION OF PURPORTED “INDIVIDUAL OVERCHARGES” USING A POOLED OVERCHARGE REGRESSION

In this hypothetical example, Customer A would have a negative “overcharge”—because it paid \$0.82 but supposedly should have paid \$0.90 in the but-for world. The other four customers would each have a positive overcharge, ranging from \$0.06 (for Customer B, with an actual price of \$0.96 and a but-for price of \$0.90) to \$0.25 (for Customer E, with an actual price of \$1.15 and a but-for price of \$0.90). An economic expert proffering this type of methodology would draw the conclusion that 80 percent (i.e., four out of five) of the proposed class members were impacted and sustained damages because of the alleged conduct, since their actual price was above their but-for price.

23. While this methodology generates seemingly individualized results (which would ostensibly be used to assess impact class member by class member), it is inappropriate to attribute the regression’s error term—i.e., the portion of the price paid in a given transaction that “simply cannot be explained by the model”²⁸—entirely and explicitly to the alleged anticompetitive conduct. Doing so contradicts the foundational premise that estimation of antitrust injury must be *causally* tied to the alleged conduct.²⁹
24. The fact that the “common impact” methodology described above not only fails to resolve the issues with the pooled overcharge approach, but also is inherently unreliable for the assessment of individualized impact, can be illustrated by the fact that it will *necessarily* show “impact” even when no anticompetitive conduct occurred. In fact, this approach will find that a substantial number of customers were “impacted” during periods of competition, when there was no “overcharge” due to any conspiracy, simply due to regression models’ inability to perfectly model actual prices.
25. **Exhibit 2** shows the same actual pricing pattern as **Exhibit 1**, but with no overcharge caused by anticompetitive conduct. That is, the “predicted actual price” in column [c] of the exhibit is the same as the “predicted but-for price”

²⁸ USING ECONOMETRICS, *supra* note 29, at 9.

²⁹ See, e.g., FED. JUD. CTR., REFERENCE MANUAL ON SCIENTIFIC EVIDENCE 432 (3d ed. 2011) (“The first step in a damages study is the translation of the *legal theory of the harmful event* into an analysis of the economic impact of *that event*.”) (emphasis added); PROVING ANTITRUST DAMAGES, *supra* note 17, at 57, 62, 130 (“Plaintiff’s damages case must be consistent with its liability case, particularly with respect to the alleged anticompetitive effect of the violation.” “In a price-fixing case, for example, there must be an analysis that provides evidence of a clear link between the agreement to fix prices and an increase in prices that is not explained by other factors.”).

in column [e]. The overcharge in column [f] is zero. In this scenario, the pooled regression model would generate the same pattern of prediction errors (in column [d] of the exhibit).

<u>Customer</u>	<u>Actual Price</u> <u>(Equation [1])</u>	<u>Predicted</u> <u>Actual Price</u> <u>(Equation [2])</u>	<u>Prediction</u> <u>Error</u> <u>(ϵ_i)</u>	<u>Predicted But-</u> <u>For Price</u> <u>(Equation [3])</u>	<u>Pooled</u> <u>Overcharge</u> <u>(β_3)</u>	<u>"Individual"</u> <u>Overcharge</u> <u>(Equation [4])</u>
[a]	[b]	[c]	[d]=[b]-[c]	[e]	[f]=1-[e] / [c]	[g]=[d]+([c]-[e])
A	\$0.82	\$1.00	-\$0.18	\$1.00	0%	-\$0.18
B	\$0.96	\$1.00	-\$0.04	\$1.00	0%	-\$0.04
C	\$0.99	\$1.00	-\$0.01	\$1.00	0%	-\$0.01
D	\$1.08	\$1.00	\$0.08	\$1.00	0%	\$0.08
E	\$1.15	\$1.00	\$0.15	\$1.00	0%	\$0.15

EXHIBIT 2. ILLUSTRATIVE CALCULATION OF PURPORTED “INDIVIDUAL OVERCHARGES” USING A POOLED OVERCHARGE REGRESSION IN THE ABSENCE OF ANTICOMPETITIVE CONDUCT

As it does in the example in **Exhibit 1**, the “common impact” methodology would simply combine the pooled overcharge (in this case, zero) with the customer-specific error terms, illustrated in column [d] of the exhibit.³⁰ The methodology would thus purport to show “antitrust impact” to Customers D and E because their actual prices were above the predicted but-for prices. Put differently, in this example, the “common impact” methodology would find 40 percent (two out of five) of class members to have been “impacted,” even though there was no anticompetitive conduct. The reason for this is that the model does not in fact estimate separate overcharges for different customers, but rather provides the appearance of customer-level analysis through the mechanical inclusion of prediction errors generated by the pooled regression model, which are not explicitly related to the effects of a conspiracy.

26. The result illustrated in **Exhibit 2** is not specific to the simplifying assumptions of this illustration. Rather, this type of methodology will consistently show such “false positive” findings of “impact” because all regressions generate error terms that are positive for approximately half of the transactions in the data set³¹—and which the methodology would incorrectly interpret as “overcharges.” This is disqualifying for this “common impact” approach, as a methodology that consistently purports to show impact where none can exist cannot be reliable.

IV. CONCLUSION

27. To date, courts have largely not engaged with the technical elements of the “common impact” methodologies described in this paper, nor with the issues raised by these methodologies. The general response from proponents of these methodologies has been that they are meant to be applied only in periods of anticompetitive conduct—and that applying them to periods where no

³⁰ Note that in the case of zero overcharge, the prediction errors in column [d] of **Exhibit 2** are the same as the purported “individual overcharges” in column [g].

³¹ Error terms, by construction, have an average value of zero across the data set. *See, e.g.,* GUJARATI, *supra* note 14, at ch. 2.4.

anticompetitive conduct existed (as a showing of the “false positive” results they generate) is somehow not relevant or appropriate. This argument, however, seems to turn the notion of statistical testing on its head.³² A reliably designed methodology should not find widespread antitrust impact when tested against a period where there is no anticompetitive conduct. One that *does* find injury that does not exist should raise red flags about its viability as proof of common impact.

³² See, e.g., Haider et al., *supra* note 3, for additional relevant discussion.