

Crémieux, Pierre-Yves; Simmons, Ian; Snyder, Edward A.

Working Paper

Proof of Common Impact in Antitrust Litigation: The Value of Regression Analysis

Working Paper, No. 231

Provided in Cooperation with:

George J. Stigler Center for the Study of the Economy and the State, The University of Chicago Booth School of Business

Suggested Citation: Crémieux, Pierre-Yves; Simmons, Ian; Snyder, Edward A. (2010) : Proof of Common Impact in Antitrust Litigation: The Value of Regression Analysis, Working Paper, No. 231, The University of Chicago, George J. Stigler Center for the Study of the Economy and the State, Chicago, IL

This Version is available at:

<https://hdl.handle.net/10419/262633>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Working Paper No. 231

**“Proof of Common Impact in Antitrust Litigation:
The Value of Regression Analysis”**

PIERRE CREMIEUX

IAN SIMMONS

AND

EDWARD A. SNYDER

**George J. Stigler Center for the Study
of
the Economy and the State
The University of Chicago**

April 6, 2010

PROOF OF COMMON IMPACT IN ANTITRUST LITIGATION:
THE VALUE OF REGRESSION ANALYSIS*

by

Pierre Cremieux*

Ian Simmons**

and

Edward A. Snyder***

* Managing Principal, Analysis Group and Adjunct Professor, Department of Economics, Université du Québec à Montréal.

** Partner, O'Melveny & Myers LLP, Washington, D.C.

*** Dean and George Shultz Professor of Economics, University of Chicago Booth School of Business.

Please send comments to:

Pierre Cremieux
Managing Principal
Analysis Group
111 Huntington Avenue, Tenth Floor
Boston, MA 02199
PCremieux@AnalysisGroup.com

Forthcoming (2010) 17 Geo. Mason L. Rev.

Acknowledgements: We would like to thank Dov Rothman for research assistance and thank Dennis Carlton, Michael Moore, and Judy Roberts for helpful comments. We would also like to thank the "George J. Stigler Center for the Study of the Economy and State" for their support.

Abstract:

Whether antitrust injury to members of a proposed class can be proven on a common, classwide basis is often critical in court decisions analyzing whether to certify antitrust class actions. Courts have been willing to rely on regressions to provide such proof but in recent cases have been unwilling to rely on mere promises that regression analysis can be done. We explore the role of regression analysis in this light. First, we examine the role of regression analysis as a tool to help isolate the impact of an alleged antitrust violation. Second, even when a regression successfully *proves* impact, we explore the circumstances in which the results should be viewed as *common* in the sense of constituting classwide evidence. We develop two relevant concepts: (a) *macro-commonality*, which concerns whether regression results are robust given the scope of the proposed class, and (b) *micro-commonality*, which concerns whether regression results indicate that common issues predominate over individual issues. We conduct two empirical inquiries using actual transaction data to illustrate the need to perform micro- and macro-commonality tests as necessary, albeit not sufficient, conditions for regression analysis to constitute a common method of proof.

1. Introduction

The class certification stage in private antitrust cases involves large and discontinuous stakes for the parties involved. Failure to have a proposed class certified “may sound the ‘death knell’” of a class action lawsuit as it virtually eliminates the incentive of at least some plaintiffs to pursue their claims because their potential individual damages are small relative to the costs of litigation.¹ In contrast, certification of the class means that defendants typically face significant aggregated claims. Given uncertainties associated with the legal process and the provisions for treble damages and one-way fee shifting in favor of successful plaintiffs, class certification often results in large settlements.² Hence, the value of the damage claims and the potential deterrence associated with private antitrust enforcement generally shift dramatically with class certification outcomes.

While other factors are relevant,³ class certification often turns on plaintiffs’ ability to demonstrate impact from the alleged violation using common proof on a classwide basis. Courts often have accepted regressions as proof of common impact but have also indicated an unwillingness to rely only on promises that regression analysis can be done.⁴ In this light, we explore the value of regression and its role in proving common impact.

¹ *Newton v. Merrill Lynch, Pierce, Fenner & Smith, Inc.*, 259 F.3d 154, 162 (3d Cir. 2001).

² See *In re Hydrogen Peroxide Antitrust Litig.*, 552 F.3d 305, 310 (3d Cir. 2009) (“In some cases, class certification ‘may force a defendant to settle rather than incur the costs of defending a class action and run the risk of potentially ruinous liability.’”) (quoting Fed. R. Civ. P. 23 advisory committee’s note, 1998 Amendments).

³ Other factors determining whether a class can be certified include numerosity of the members of the proposed class, adequacy of counsel for plaintiffs, and the lack of conflict among members of the proposed class. See Section II for further discussion.

⁴ For example, in *Piggly Wiggly Clarksville Inc. v. Interstate Brands Corp.*, 100 Fed. Appx. 296 (5th Cir. 2004), the Fifth Circuit “criticiz[ed] plaintiffs’ expert for simply opining that he could find a formula to calculate damages using multiple regressions, rather than offering an actual model for doing so” in affirming the district court’s denial of class certification. Gregory C. Cook and Charlton A. Rugg, “Tightening Trends in Antitrust Class

In Section II, we assess the legal environment, focusing on the differences among courts in their views of regression methods. This discussion establishes that courts are less likely to accept expert opinions that regression methods are available to demonstrate common impact and are moving from a presumption in favor of plaintiffs to a more critical posture towards establishing proof of classwide impact.

In Section III, we review regression analysis as a set of tools to prove impact on a common basis. To constitute *proof*, the relevant regression estimates should demonstrate impact, identify the class members who are impacted, and provide a method to measure the extent of damages, if any. In Section IV, we focus on the issue of regression results as *common proof* of impact in the sense of representing classwide evidence. We introduce and explain two concepts that are useful in evaluating regression results:

- a. *macro-commonality*, meaning that the results are robust given the scope of the proposed class, and
- b. *micro-commonality*, meaning that common issues predominate over individual issues.

In this section, we conduct two empirical analyses to explore these issues and illustrate the difference between proof of impact and common proof of impact.

In Section V, we consider the importance of testing for commonality in light of relevant insights from the well-developed literature on cartels. Specifically, even when (a) horizontal competitors entered into an illegal agreement, and (b) the agreement impacted some purchasers, it cannot be assumed that all purchasers were impacted because of incentives for individual competitors to deviate from the agreement and the complexity of maintaining and enforcing horizontal agreements. Thus, even an effective agreement may result in disparate impact across

Certification,” *The Antitrust Practitioner*, July 2006, p. 4. See also *Blades v. Monsanto Co.*, 400 F.3d 562, 570 (8th Cir. 2005).

4. See also *Blades v. Monsanto Co.*, 400 F.3d 562, 570 (8th Cir. 2005).

some purchasers and no impact for others.⁵ This discussion underscores the importance of distinguishing between results that constitute proof and those that constitute common classwide proof.

In Section VI, we offer concluding remarks on how regression analyses should be evaluated in the context of antitrust class action claims and the role that micro- and macro-commonality tests can play in determining whether regression analysis constitutes a common method of proof.

II. Legal Context and the Willingness of Courts to Accept Regression Methods as a Means of Providing Common Proof

Section 4 of the Clayton Act provides a private right of action for antitrust claims.⁶ The Act provides for treble damages and one-way fee shifting when plaintiffs prove that they have been impacted, *i.e.*, injured by an antitrust violation, thus “evinc[ing] classic tort principles of injury and damages flowing from and proximately caused by, a violation of substantive law.”⁷ Even when there is evidence of a *per se* antitrust violation such as price fixing (civil suits often follow the announcement of a guilty plea negotiated with the U.S. Department of Justice), private plaintiffs must still prove individual injury proximately caused by the price fixing and measurable damages.⁸ These cases frequently proceed as putative class actions, with Federal Rules of Civil Procedure 23(a) and 23(b)(3) setting forth the requirements for certification of the

⁵ Michael D. Whinston, LECTURES ON ANTITRUST ECONOMICS (2008) at 26-39 (noting that existing literature “offers less evidence than one might think” that preventing oligopolists from talking has a substantial effect “on the price they charge.”)

⁶ 15 U.S.C. § 15.

⁷ Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” ANTITRUST, Summer 2007, p. 61.

⁸ See, e.g., *In re Hydrogen Peroxide Antitrust Litig.*, 552 F.3d 305, 311 (3d Cir. 2008); *Blades v. Monsanto Co.*, 400 F.3d 562, 566 (8th Cir. 2005); *Simpson v. Union Oil Co.*, 311 F.2d 764, 767 (9th Cir. 1963).

proposed class.⁹ The extent to which questions of law and facts are common to the claims and the extent to which these common elements predominate over individualized elements together form a critical nexus of decision-making around class certification.

Courts increasingly scrutinize at the class certification phase whether plaintiffs were injured by the alleged conduct, with particular emphasis on whether plaintiffs can show classwide injury using a common method of proof.¹⁰ The *Monsanto* court defined common proof as follows:

The requirement of Rule 23(b)(3) that common questions predominate over individual questions tests whether proposed classes are sufficiently cohesive to warrant adjudication by representation. The nature of the evidence that will suffice to resolve a question determines whether the question is common or individual. If, to make a prima facie showing on a given question, the members of a proposed class will need to present evidence that varies from member to member, then it is an individual question. If the *same* evidence will suffice for each member to make a prima facie showing, then it becomes a common question.¹¹

Yet, courts have diverged substantially with respect to the burden plaintiffs must satisfy at the class certification stage. Much of this confusion originated from the Supreme Court's conflicting instructions that (i) "nothing in either the language or history of Rule 23 . . . gives a court any authority to conduct a preliminary inquiry into the merits of a suit in order to determine

⁹ Under Rule 23(a), plaintiffs must show that: (i) there are questions of law or fact common to class members (commonality); (ii) the claims of the named plaintiffs are representative of those of other proposed class members (typicality); (iii) the number of proposed class members is so large that handling the cases individually would be unworkable (numerosity); and (iv) the plaintiff's lawyers will represent the proposed class adequately (adequacy of representation). Under Rule 23(b)(3), plaintiffs must show that: (i) issues of fact and law for the class predominate over issues of fact and law affecting only individual class members (predominance); and (ii) a class action is better than alternative means of judicial treatment such as individual cases or test cases (superiority).

¹⁰ See, e.g., *Castano v. Am. Tobacco Co.*, 84 F.3d 734, 744 (5th Cir. 1996) ("Going beyond the pleadings is necessary, as a court must understand the claims, defenses, relevant facts, and applicable substantive law in order to make a meaningful determination of the certification issues."); see also *Weisfeld v. Sun Chem. Corp.*, 210 F.R.D. 136, 143 (D.N.J. 2002), *aff'd* 84 F. App'x 257 (3d Cir. 2004) ("common proof must adequately demonstrate damage to each individual."); *In re Universal Serv. Fund Tel. Billing Practices Litig.*, 219 F.R.D. 661, 678 (D. Kan. 2004) ("common issues do not predominate every horizontal price-fixing antitrust claim").

¹¹ *Blades*, 400 F.3d at 566 (citations omitted) (emphasis added).

whether it may be maintained as a class action,”¹² and (ii) a class action “may only be certified if the trial court is satisfied, after a rigorous analysis, that the prerequisites of Rule 23(a) have been satisfied.”¹³ Lower courts have struggled in the wake of these rulings to conduct a “rigorous analysis” of class certification elements without engaging in a “preliminary inquiry” about factual and legal issues that bear on the merits of the case.¹⁴

Embedded in this broader struggle was the role of expert opinion at the class certification stage. Until recently, courts outside the Fourth, Fifth, and Eleventh Circuits often undertook little to no analysis of expert opinion. The Third Circuit’s decision in *In re Hydrogen Peroxide Antitrust Litigation* in late 2008 vacating a grant of class certification, was an important development in the trend of analyzing expert opinion at the class certification stage as part of a broader rigorous analysis.¹⁵ The Third Circuit’s decision was a watershed moment given its earlier decision in *Bogosian v. Gulf Oil Co.*, in which it held that if plaintiffs prove a nationwide conspiracy resulting in increased prices to a class of plaintiffs, an individual plaintiff could show damages simply by proving that the free market prices would have been lower than the prices paid and that he made some purchases at the higher price.¹⁶ Some courts have applied this “*Bogosian* short-cut” to find that plaintiffs can prove impact and injury on a classwide basis.¹⁷

In re Hydrogen Peroxide is further evidence of the trend that has emerged following the Supreme Court’s 1997 ruling in *Amchem Products v. Windsor* that lower courts must take a

¹² *Eisen v. Carlisle & Jacquelin*, 417 U.S. 156, 177 (1974).

¹³ *Gen’l Tel. Co. of the Southwest v. Falcon*, 457 U.S. 147, 161 (1982).

¹⁴ For a more detailed discussion of this struggle, see Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” *ANTITRUST*, Summer 2007.

¹⁵ *In re Hydrogen Peroxide*, 552 F.3d at 305.

¹⁶ 561 F.2d 434 (3d Cir. 1977).

¹⁷ See, e.g., *In re Linerboard Antitrust Litig.*, 203 F.R.D. 197, 208 (E.D. Pa. 2001) (following *Bogosian* and granting plaintiffs’ motion for class certification); *aff’d* 305 F.3d 145 (3d Cir. 2002); *In re Microcrystalline Cellulose Antitrust Litig.*, 218 F.R.D. 79, 89-93 (E.D. Pa. 2003) (same); *In re Mercedes-Benz Antitrust Litig.*, 213 F.R.D. 180, 188-189 (D.N.J. 2003) (same); *In re Art Materials Antitrust Litig.*, 38 Fed. R. Serv. 2d (Callaghan) 1509 at *12 (N.D. Ohio 1983) (same); *Rental Car of New Hampshire, Inc. v. Westinghouse Electric Corp.*, 496 F.Supp. 373, 381-382 (D. Mass. 1980) (same)..

“close look” at the predominance and superiority factors in Rule 23(b)(3).¹⁸ Since *Amchem*, courts to varying degrees have gravitated towards an emerging consensus that: (i) plaintiffs must show that the Rule 23 requirements are met by a preponderance of the evidence; and (ii) the district court must rigorously examine whether the plaintiffs have met these requirements. Review at the class certification stage may include issues related to the merits of the case and competing expert testimony, as well as insisting that the plaintiff submit a methodology that can show classwide impact using common proof in the context of the case.¹⁹ For example, the Third Circuit explained that “the court’s obligation to consider all relevant evidence and arguments extends to expert testimony, whether offered by a party seeking class certification or by a party opposing it.”²⁰ (Recent rulings in the circuit courts are summarized in the Appendix.)

As a result, courts increasingly are skeptical of experts who do not offer a functioning model tailored to the facts of the case.²¹ This trend has manifested itself in a series of cases in which plaintiffs have tendered various regression models. For example, in *Freeland v. AT&T Corp.*, the district court found serious defects in the expert’s proposed methodology, ruling that his regression model was “so incomplete as to be inadmissible” and denying class certification.²²

¹⁸ Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” *ANTITRUST*, Summer 2007, p. 63. This reassessment accelerated in 2003 when the standard in Rule 23 for ruling on class certification was changed from “as soon as is practicable” to “at an early practicable time.”

¹⁹ See Gregory C. Cook and Charlton A. Rugg, “Tightening Trends in Antitrust Class Certification,” *The Antitrust Practitioner*, July 2006, pp. 2-5; and Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” *ANTITRUST*, Summer 2007, pp. 61-68.

²⁰ *In re Hydrogen Peroxide*, 552 F.3d at 307. A good example of a court scrutinizing expert testimony, even when it overlaps with the merits, is *Behrend v. Comcast Corp.*, 2010 WL 46856 (January 7, 2010).

²¹ See also Gregory C. Cook and Charlton A. Rugg, “Tightening Trends in Antitrust Class Certification,” *The Antitrust Practitioner*, July 2006, pp. 2-5.

²² 238 F.R.D. 130, 149 (S.D.N.Y. 2006) (observing that the proposed regression analysis omitted at least two significant variables and that plaintiffs’ arguments for excluding those variables were unpersuasive).

In *Piggly Wiggly Clarksville, Inc. v. Interstate Brands Corp.*, the Fifth Circuit likewise denied class certification, criticizing plaintiffs' expert for claiming but not demonstrating that he could use regression analysis to calculate damages because he did not explain how he would model certain factors.²³ The Second Circuit went a step further with respect to the requirement of conducting a rigorous analysis in *Cordes & Co. Financial Services v. A.G. Edwards & Sons, Inc.* After vacating the district court's denial of class certification and rejection of plaintiffs' expert submission, the Second Circuit instructed the district court to push the experts to conduct dry runs of their models using the facts of the case.²⁴ More recently, the Third Circuit continued the trend by vacating the district court's order certifying the class in *In re Hydrogen Peroxide* and finding plaintiffs' and defendants' expert analyses — including a regression analysis tendered by plaintiffs' expert — “irreconcilable.”²⁵ Despite plaintiffs' expert representation that “sufficient reliable data” existed for the regression analysis,²⁶ defendants' expert countered that the analysis would need to incorporate “a multitude of different ‘variables’” given industry-specific facts, thus rendering common proof impossible.²⁷

As courts pay closer attention to the methodologies and arguments offered by economic experts, including assessing more critically the scientific validity and applicability of proposed regression analyses to the individual facts of each case, an understanding of regression's strengths and weaknesses in the class certification context becomes more important. In the next

²³ 100 Fed. Appx. 296, 299-301 (5th Cir. 2004), aff'g 215 F.R.D. 523 (E.D. Tex. 2003) (“Multiple regression analysis is not a magic formula. It is simply a mathematical tool . . . which may or may not yield statistically significant results.”).

²⁴ 502 F.3d 91, 107 (2d Cir. 2007) (“If the plaintiffs' single formula can be employed to make a valid comparison between the but-for fee and the actual fee paid, then it seem sto us that the injury-in-fact question is common to the class. Otherwise, it poses individual ones. The district court did not determine which expert is correct. We leave this question for it to resolve on remand.”).

²⁵ *In re Hydrogen Peroxide*, at 314, 325.

²⁶ *Id.* at 313.

²⁷ *Id.* at 314.

two sections we address the general value of regression methods in yielding proof of impact, and then turn to the issues concerning commonality of proof.

III. Proof of Impact

In the context of suspected cartel pricing behavior, economists use regression methods to identify various non-collusive factors which may affect the prices paid by members of the proposed class, and isolate the potentially common effect of a horizontal conspiracy. In this way, regressions may provide proof of impact despite differences in prices resulting from non-collusive factors, some of which may be specific to individual members of the proposed class.

The most important econometric requirement in this context is that the relevant regression estimates isolate and quantify the effect of the alleged antitrust violation. A regression intended to prove the causal effect of a price-fixing conspiracy on prices must reliably estimate the unobserved prices that would have been paid but for the alleged conspiracy. To achieve these objectives, the *regression specification* – which refers to the variables included in the regression and the form of the regression – must reflect the facts in the case and the specifics of the industry at issue.²⁸ For example, prices from a benchmark market may be used to proxy for but-for prices. Similarly, prices paid before (and/or after) the alleged violations may be used in a before-and-after analysis.²⁹

Neither competitive benchmarks nor before- or after-periods, generally will be identical to an allegedly collusive market. One would not necessarily expect prices in a before period to

²⁸ For related discussions, see Jonathan Baker and Daniel Rubinfeld, “Empirical Methods in Antitrust Litigation: Review and Critique,” *American Law and Economics Review*, 1999, pp.386-435; and Franklin M. Fisher, “Multiple Regression in Legal Proceedings,” 80 *Columbia Law Review*, 1980, p. 729.

²⁹ For example, in *Cordes*, an antitrust case in which plaintiffs claimed defendants conspired to fix IPO underwriting fees, plaintiffs’ expert asserted that he could derive a common formula for calculating but-for fees by establishing a benchmark fee from a set of prices paid in temporal or geographic isolation from the alleged conspiracy, and use regression analysis to isolate the explanatory variables that influence the benchmark fee.

be accurate proxies for current but-for prices given potential changes in demand and supply conditions, product features, and inflation. Any method, including regression, should control for differences that are unrelated to the alleged collusion.³⁰ When a well-specified regression controls for the differences, the results may indicate impact. However, if the set of control variables is incomplete or poorly defined, experts should explain their choice of the particular factors included as well as the reasons for not including others.³¹ This requires a thorough understanding of the industry, pricing practices, and relevant institutional factors. Failure to consider and include factors that influence prices, and are positively correlated with the alleged conspiracy will yield an overestimate of the impact of the alleged conspiracy. In basic scientific terms, the regression would fail to isolate the effect of the conspiracy from other unrelated factors and, as a result, concatenate the two effects and fail to provide proof of impact.

To further explore the issue of commonality in the context of class certification, it is necessary to lay some groundwork on alternative regression specifications should be laid. In its most basic form, a regression equation may describe a linear relationship between two or more variables:

$$(1) \quad Y_i = a + bX_i + e_i,$$

³⁰ These controls could include inflation, seasonality variables, and changes in the prices of substitutes and complements.

³¹ One Treatise states:

Plaintiffs using regressions for class certification purposes will generally try to control for various customer attributes. But these attributes are not always accurately captured in regressions because of data limitations or problems with the specification of the regression. For example, if individual customers qualify for volume discounts at some times but not others, the regression would need to take this into account. Similarly, if delivery charges are added to prices at some times and not others or the types of products offered and purchased change over time, it would be improper to use time-series data or models that do not reflect these variations over time. When there is substantial variation in fundamental aspects of the price data of this type, individual inquiries are necessary to understand the factors that shaped the price that specific customers paid.

ABA Section of Antitrust Law, *Econometrics: Legal, Practical, and Technical Issues*, 224 (ABA Publishing 2005).

where Y is the dependent variable (e.g., price), a the constant term which does not vary with different values of Y_i , X is the independent or explanatory variable (e.g., product characteristics), b the coefficient that captures the relationship between X and Y , and e is the error term. The subscript i denotes a transaction and illustrates the fact that the regression will capture the relationship between Y and X across multiple transactions. The implicit assumption is that X influences Y . In a non-antitrust setting, if X measured a person's job experience and Y measured compensation, the equation would specify a relationship in which compensation depends on experience based on observations on i individuals.

Estimation of the regression yields the best fit of the available data and thus identifies the central (or average) tendency in the relationship between job experience and compensation. The effect of additional years of experience on compensation is reflected in the estimated coefficient, b , whose positive value might indicate that compensation increases with experience.³² Whether the estimated regression is a good fit would be reflected in the overall explanatory power of the regression, which in this context will be determined in part by the statistical significance of b .³³ In general, a regression is more likely to yield statistically significant coefficients when there is more systematic variation in the underlying data and when the number of observations in the data set is larger. However, the exclusion of relevant variables, here, gender, age or other individual characteristics, may result in a misinterpretation of the relationship between compensation and experience.

³² This statement is conditional on how compensation and job experience are measured. When comparing the values of estimated coefficients across regressions, one needs to account for whether the underlying variables are measured in the same way.

³³ Note that in a multivariate regression (i.e., a regression that includes more than one explanatory variable) the overall explanatory power of a regression and the statistical significance of the estimated coefficients may not be as closely related. In particular, when the explanatory variables are themselves highly collinear their estimated coefficients will often not be statistically significant even though the overall explanatory power of the regression may be high.

We now turn to a similar example in an antitrust context where the objective is to assess how product prices in New York compare to those in San Francisco. A regression similar to equation (1) could be specified in which the dependent variable Y is price and the independent variable X is an indicator or dummy variable that equals 1 for New York and 0 for San Francisco. Estimating this version of equation (1) is equivalent to calculating the average price in New York and the average price in San Francisco, and then computing the difference between the two averages. The intercept term a identifies the average price in San Francisco, the coefficient b is the difference in average prices between New York and San Francisco and the sum of a and b is the average price in New York.

The value of regression in this context is that it can facilitate more sophisticated comparisons of averages. Suppose, for example, that the data covered sales of two versions of the product, a basic and an enhanced version. *Multivariate* regression analysis can account for additional factors:

$$(2) \quad Y_i = a + bX_i + cV_i + e_i.$$

Compared to equation (1), this specification adds another dummy variable, V , that equals 1 for the enhanced product and 0 for the basic product, and thereby provides an estimate of the difference between average prices in New York and San Francisco after controlling for differences in product mix across the two cities.

This case is highly relevant to the issue of common proof in class certification. Equation (2) only specifies a single coefficient, b , to capture the effects of location on prices. Hence, this specification embodies the assumption that the price differences between New York and San Francisco are the same for the basic and enhanced products. Indeed, this specification actually imposes the *condition* that the price differences between the two products must be the same. Put

in legal terms corresponding to the framework associated with class certification, *this specification assumes rather than tests that there is a common effect of location on the price differences for the two products*. If this type of a regression were used to investigate the effects of a conspiracy affecting the sales of both product versions in New York, with San Francisco as a potential benchmark city, the specification would embody the assumption of commonality across the two product types. The regression would produce an *average* of the price differences between the two products across the two cities; it could not reveal whether there were important differences between the price effects of location on the prices of the basic and enhanced products.

In general, an expert opinion on class certification issues should test rather than assume that the effects of an alleged violation are common across products and other relevant dimensions. A more sophisticated regression model might do so. Equation (3) below is identical to equation (2) except that an interaction term, constructed by multiplying the city indicator (X) by the product indicator (V), has been added. This term equals 1 for the prices of the enhanced version sold in New York.

$$(3) \quad Y_i = a + bX_i + cV_i + d[X_i * V_i] + e_i.$$

With this specification, the differences in average prices for the enhanced and basic products across the two cities can be estimated separately in a single regression. The coefficient b is the difference in average prices for the basic version and the sum of the coefficients b and d is the difference in average prices for the enhanced version. If d is significantly different from zero, the effect of the conspiracy (assuming that nothing other than the conspiracy explains differences across the two cities) is different across the two products. A single estimate of the conspiracy's effect on the products, as would have been generated by equation (2), would not have accurately

captured the conspiracy's impact. In our terminology, this result would have failed the *macro-commonality* test. Specifically, such a simplified test could aggregate injured and uninjured proposed class members with no method to distinguish between the two. If, however, equation (3) yielded the result that d was equal to zero, then the assumption of macro-commonality across product types may be correct. We explore these issues further in Section IV(a).

Even when a regression result supports the assumption of macro-commonality across product types, whether the central tendency in the data applies to individuals in the data can be explored by evaluating how well the regression predicts results for individuals and how well the regression identifies the effect of the alleged conspiracy on individuals within the proposed class. With one independent variable, this would involve identifying the prices paid by individual class members given the type of product purchased. If a regression predicts precisely the outcome of interest (here price) for most individual cases, then the estimated relationship would, in our terminology, meet the *micro-commonality* test. In other words, regression (1) may precisely identify the price paid by each individual member of the class across the two cities. If, however, factors such as location of purchase and volume purchased are highly influential and omitted from the regression, the price predicted by the regression based on product type alone could deviate substantially from the observed price. Similarly, even if other factors have not been omitted if the average impact of the city on price measured through the regression masks great variation across members of the class, then the estimated relationship would not meet the *micro-commonality* test. We explore these issues further in Section IV(b).

IV. Commonality

As indicated by the preceding section, regression methods yield central tendencies. A well-specified regression might provide proof that prices in one market are higher on average

than prices in another market. Class certification, however, requires inquiry into potential differences among proposed class members, not merely evidence of average impact. An expert should prove that impact as estimated by regression does not combine cases of injury to individual class members with cases of non-injury.³⁴ In this section we deal with macro-commonality, which focuses on the relevance of regression results across proposed sub-classes (e.g., different time periods, different products), and then with micro-commonality, which focuses on the relevance of regression results for individual members of the proposed class.

a. Macro-Commonality

In this subsection, we focus on whether a regression offers common proof of impact in the sense of providing valid results for various *subsets* of observations. Hence, the focus with macro-commonality is whether impact can be confirmed across various subsets of the proposed class. Starting from an overall finding of impact, a test of macro-commonality focuses on re-estimating the regression to determine whether the estimates of impact are confirmed across subgroups of the proposed class. If a statistically significant result for the proposed class as a whole does not hold up when the class is divided, *i.e.*, the impact results are not established across subgroups, then the original regression by itself should not be viewed as demonstrating common impact.

We explore the issue of macro-commonality using data on actual rum prices across cities in the United States.³⁵ The analysis begins with the presumed allegation that manufacturers

³⁴ See, e.g., *In re Hydrogen Peroxide*, 552 F.3d at 311 (“[I]ndividual injury (also known as antitrust impact) is an element of the cause of action; to prevail on the merits, every class member must prove at least some antitrust impact resulting from the alleged violation.”).

³⁵ The data are provided by The Nielsen Company and cover weekly dollar and quantity sales volume for forty product specifications of rum liquor from 1996 through 2000. The data are granulated by week, product specification, location, and store type. Quantity units are given in cases of the given specification. Average price per liter is calculated as sales divided by quantity and then divided by the number of liters in a case of the given specification. Case liters are determined by the bottle volume of the specification (e.g., a case of 750ml bottles will

colluded to raise prices in five cities: Tampa, New York, Denver, Miami, and Boston. Another set of seven cities (Atlanta, Chicago, Kansas, Miami, Minneapolis, San Diego, and San Francisco) has been assumed to constitute a valid competitive benchmark. Could a regression analysis establish common proof of impact to an indirect purchaser class of rum consumers suing for damages? Naturally, the purpose of this regression would be to prove that the prices paid by rum purchasers in the cities subject to the collusive behavior were higher than the prices paid in the benchmark cities.³⁶

We first regress the retail prices on an indicator variable that equals 1 for the allegedly collusive cities and zero for the proposed benchmark cities as well as other independent variables controlling for:

- i. Year (1996 through 2000)
- ii. Store type (drug store, discount store, liquor store, Hispanic neighborhood store),
- iii. Brand (Bacardi, Castillo, Captain Morgan, Malibu, Myers's, and RonRico)
- iv. Liquor type (flavored, gold, light, proof 151), and
- v. Product size (375 ml., 750 ml., 1,000 ml., and 1,750 ml.).³⁷

The estimated coefficient for the indicator variable for the cities subject to the alleged conspiracy is \$1.10 and statistically significant.³⁸ Thus, accounting for store type, rum type, bottle size, and

contain a total of nine liters or twelve bottles). This price per liter is then adjusted to exclude state sales and excise taxes. Tax data are from www.taxadmin.org. Price per liter net of tax is adjusted to reflect cross-location differences in food price levels. These data come from a B.E.A. working paper authored by Bettina Aten. "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005, p. 12. Note that these data reflect inter-area levels of food (not food and beverage) prices as of 2003. The Bureau of Labor Statistics (Aten's data source) does not publish inter-area figures. .

³⁶ For ease of exposition, the regression results presented here are based on a simple least squares regression with no effort to correct for potential statistical issues such as heteroskedasticity, autocorrelation, normality of the distribution of the dependent variable, etc. As such, it should be seen only as an example of a potential approach to regression analysis.

³⁷ Thus, in equation form the regression is:

$$P_{it} = a + b_1 Collude_t + b_2 StoreType_t + b_3 Brand_t + b_4 RumType_t + b_5 BottleSize_t + b_6 Year_t + e_{it}$$

Where *i* refers to the transaction characteristics that correspond to each observed price (i.e., city, store type, brand, liquor type and product size).

year, the average price per liter of rum was approximately \$1.10 higher in the allegedly collusive cities than in the proposed benchmark cities. Table 1 reports the regression results.

Assuming that the regression result is valid and reflects, for example, insights from the evidentiary record, let us now evaluate whether it meets the *macro-commonality* test. The \$1.10 coefficient on the conspiracy variable in the original regression indicates only that prices were higher *on average* in the five cities subject to the alleged collusion compared to the seven benchmark cities. Should this finding be viewed as common proof of illegal overcharges? For example,

- i. Did the conspiracy lead to higher prices in each of the five collusive cities?
- ii. Did the conspiracy lead to higher prices on the different branded products subject to the conspiracy?
- iii. Did the conspiracy lead to higher prices in each year during the collusive period?

In other words, is the finding that members of the class were impacted, irrespective of the year of their purchase, the type of product purchased or the city in which they purchased the product?

To investigate the first question, we can estimate an alternative regression with indicator variables for each of the allegedly collusive cities rather than a single indicator for all five cities. This regression, as reported in Table 2, yields the following estimated coefficients, each of which is statistically significant: -\$0.99 for New York; \$0.71 for Boston; \$0.98 for Miami; \$1.36 for Denver; and \$3.47 for Tampa. These results indicate a lack of commonality across cities, with differences between the allegedly collusive cities and the set of benchmark cities from -\$0.99 to \$3.47. The original regression, with the single coefficient of \$1.10, dramatically underestimates the alleged conspiracy's impact on average prices in Tampa and dramatically overestimates the

³⁸ Statistical significance here indicates whether the hypothesis that a given estimate is equal to zero can be rejected at the 5 percent level of confidence.

impact in New York. These results suggest potential inconsistencies about the allegations of conspiracy. Why do the alleged overcharges differ so much and why are but-for prices actually higher than the actual prices in New York? Given this lack of commonality, a natural step would be to estimate the alleged conspiracy's effects on prices separately for each of the allegedly collusive cities.³⁹

Regarding the issue of macro-commonality across branded products, the regressions to this point implicitly have assumed that overcharges are common across products. In principle, however, the alleged conspiracy could have yielded different overcharges across products due to differences in manufacturer adherence to the terms of the conspiracy. In addition, pass-on behaviors by distributors and retailers could vary by brand because of varying demand characteristics.⁴⁰ To further investigate macro-commonality, we modified the regression to estimate *brand-specific overcharges by city*. In the case of Boston, where the city-specific overcharge per liter had been estimated at \$0.71, the estimated overcharges by brand are as follows: \$0.56 for Bacardi; \$1.07 for Castillo; \$1.61 for Captain Morgan; \$0.55 for Myers; and -\$0.26 for RonRico. As reported in Table 3, only the coefficient for Castillo is statistically significant. These results indicate, therefore, that the city-specific overcharge is itself not

³⁹ Further analysis raises additional doubts in this regard. Suppose that the proposed benchmarks were limited to three cities – Atlanta, Kansas City, and San Diego – and the others were dropped. When the modified regression is estimated, the coefficient on the conspiracy indicator drops to a statistically insignificant value (-\$0.12.) Alternatively, if the proposed benchmark cities are San Francisco, Chicago, Los Angeles and Minneapolis, the coefficient increases to \$2.64 and statistically significant. Clearly the choice of benchmark matters but the regression model itself provides no assistance here – there is no statistical test to differentiate between the three alternative specifications described above. (It is important not to confuse the existence of specification tests and the ability to test between alternative competitive benchmarks. For example, a specification test that compares the fit of the three alternative specifications would have no relevance to the choice of competitive benchmark.)

⁴⁰ "The problem of proof in an indirect purchaser case is intrinsically more complex, because the damage model must account for the actions of innocent intermediaries who allegedly passed on the overcharge." William H. Page, "The Limits of State Indirect Purchaser Suits: Class Certification in the Shadow of Illinois Brick," 67 *ANTITRUST L.J.* 4, 12, 1999-2000.

common and masks the lack of statistically significant results for all but one brand.⁴¹ The patterns are similar across cities with some brands showing statistically elevated prices while others do not.⁴²

To investigate commonality across years, a regression is specified to account for year-specific effects. These results are reported in Table 4 for the Castillo brand in each city. Focusing on Boston again, the overcharge is \$1.38 in 1996; \$1.49 in 1997; \$1.20 in 1998; \$0.87 in 1999; and \$0.50 in 2000. Of these, only the 1996 result is statistically significant. The lack of a statistically significant finding in most years may result from insufficient data but it does indicate that the original regression does not meet the macro-commonality test.

This empirical analysis illustrates potential challenges associated with using regression in the class certification context even when an overall finding of impact, i.e., a \$1.10 overcharge across all cities, brands and years, can be demonstrated. When city-specific differences were estimated, the estimated overcharges ranged from -\$0.99 to \$3.47. When brand-level differences were estimated for one city, Boston, the estimated overcharges ranged from -\$0.26 to \$1.61, neither statistically significant, illustrating how the city-level estimate of \$0.71 for Boston masks considerable brand-level differences. When year-level differences were estimated for one brand, Castillo, in Boston, the estimated overcharges ranged from \$0.50 (not statistically significant) to \$1.49, illustrating how the city-brand level estimate of \$1.07 for Castillo masks considerable temporal differences.

Even though the original regression did not constitute proof of common impact given the scope of the proposed class, one might argue that the analysis presented above demonstrates the

⁴¹ For Myers's, Bacardi and Captain Morgan, the estimated difference is greater than zero but not statistically significant, which means that the hypothesis that the true difference is zero cannot be rejected. The regression estimates are not precise enough for anything meaningful to be said about them.

⁴² The lack of statistical significance in some cases may be due to small sample sizes but it should be noted that each of the regressions uses hundreds of observations.

existence of a common method to demonstrate impact in some cases. From the results in Table 4, for example, one might conclude that purchasers of the Castillo brand in Tampa in 1997-2000, in Denver in 1996, and in Boston in 1996 were impacted. This line of argument leads, of course, to assessing the value of regression methods in identifying potential sub-classes. In a similar vein, it might be argued that regression methods could be used after a broad class was certified to sort out those who were impacted from those who were not.

The issues associated with using regression for more limited purposes are similar to those associated with using regression to provide common proof of impact on a classwide basis. In principle, a disaggregated analysis may provide proof of common impact within a subgroup. Our exploration of the macro-commonality issues in this setting, however, points to some hazards in relying on regression for more limited purposes. The empirical inquiry demonstrates that even at fine levels of disaggregation, impact on prices is not common. Further disaggregation, for example by size of product, could reveal that some purchasers of Castillo brand rum in 1997 in Tampa were impacted and others were not. Such findings may lead to the conclusion that individualized inquiry is needed to determine impact. The more general implication is that the expert must rely on relevant theory and facts to specify a proper regression and then test whether the average result yielded by the regression reflects commonality across various levels of aggregation or whether it masks individualized variation not prone to analysis using regression methods.

b. Micro-Commonality

To explore the issue of micro-commonality, we analyze a small hypothetical data set from an alleged price-fixing conspiracy in which a regression demonstrates that prices paid by

purchasers as a group increased following a collusive price increase announcement. These results do not constitute *common* proof unless they can be proven to demonstrate impact to individual members of the proposed class. This analysis illustrates in vivid terms that coefficients generated by regression methods reflect the central tendencies in data and, even when the results are statistically significant, the findings may not mean that the common result predominates over individual-specific factors.

This alleged conspiracy concerns the effects of announced price increases by four sellers (S-1 through S-4) on purchases by six customers (C-1 through C-6). S-1 and S-2 sell two products while S-3 and S-4 sell only one product. Announced price increases were \$0.03 for S-1's two products and \$0.05 for all other products. The effective dates of the announced price increases are shown in Table 5, which also lists the thirty transactions including invoice price, customer, seller, product, and whether the transaction took place before or after the effective date of the announced price increase.

Within the data reported in Table 5, there are natural groupings of observations for which the identities of the customer, the seller, and the product are the same. The first five observations, for example, concern C-1's purchases of Product-1A from S-1. The first three of these transactions occurred before S-1's 2/1/1999 price increase announcement. The fourth and fifth occurred after this announced increase. This timing difference is captured by the indicator variable; the Price Announcement variable in the last column of Table 5 takes on the value 0 if the transaction is before the announcement and 1 if it is after the announcement.

Multiple regression analysis of these data would find the best fit and, in principle, estimate the effect of the price announcements on actual prices paid by the six customers while accounting for other factors such as the identities of the customers, who might have differing

buying power.⁴³ More precisely, the coefficient on the Price Announcement variable would estimate the average change in transaction prices after announced price increases went into effect. If the underlying data show transaction price increases after the announcements, the estimated coefficient will be positive. If transaction prices stay the same following the announcements, the estimated coefficient will be zero.

Table 6 reports regression results. Along with the Price Announcement variable, the regression includes dummy variables for the six customers.⁴⁴ The estimated impact of the Price Announcements is slightly above \$0.02 and statistically significant; it corresponds to about 2% of the average prices before the effective dates of the announced price increases. Therefore, assuming that the announced price increases were the result of an illegal conspiracy, the regression yields statistically significant proof of impact.

These regression results and the coefficient on the Price Announcement variable should not, however, be taken as common proof of impact. Referring back to the transaction data in Table 5, and even assuming that no relevant factors have been omitted, they reflect an averaging of cases of impact and no impact -- from the point of view of individual customers. Focusing on observations 6 through 10 and observations 16 through 20, actual prices paid by customers C-2 and C-4 do not increase following the effective dates of the price announcements. When

⁴³ Given that the allegations concerns a conspiracy to increase prices whereby sellers would publicly announce price increases and then implement them, several specification questions arise. Most fundamental is the question of whether it is correct to interpret the results of the regression as evidence that the alleged conspiracy caused the price announcements and, in turn, resulted in illegal overcharges. The regression might be premised on the assumption that the conspiracy existed and that it resulted in announced price increases that were higher than they otherwise would be. A related issue concerns timing and, more specifically, the dating of the beginning of the alleged conspiracy. More general issues concern whether the effects of the price announcements have been isolated from other influences such as changes in the prices of substitutes and complements and overall demand for the products in question.

⁴⁴ C-1 is the omitted variable from the set of customer dummy variables. Given the small size of the data set, it is not possible to include either product dummy variables or seller dummy variable along with the customer dummy variables. Limitations on the number of dummy variables are common and arise when data sets are small and when the actual observations do not include sufficient variation across the categories implied by the dummy variables.

transactional data exhibit these patterns, it is likely that a multiple regression analysis will serve only to mask the underlying mix of impact and no impact cases.

This empirical inquiry illustrates how regression results that offer proof of impact can fail the *micro-commonality* test: The central tendency estimated by regression methods may not apply to particular observations or, stated in terms of class certification, statistically significant indications of impact do not necessarily apply to individual members of the proposed class. While inspection of the underlying data was sufficient in this case to indicate the problem, the more general approach to testing for micro-commonality is to (a) evaluate the overall power of the regression and the strength of the results concerning the alleged violation, and (b) compare predictions from the regression for specific individuals with actual prices.

Goodness of fit and a combination of the economic and statistical significance of the estimated impact will provide a general indication of the strength of the regression results and of the likelihood that common factors predominate over individual factors. The second step, comparing what the regression predicts for individuals with actual results, provides a more concrete sense of whether the regression represents common proof. For example, in the context of a price-fixing allegation, if there is a substantial frequency of cases where the actual prices paid by customers are equal to or far below the predicted but-for prices, then the regression results should not be interpreted as common proof of impact.

c. Implications of Macro- and Micro-Commonality Tests

Courts across the country have applied different standards for class certification. Not surprisingly given this context, economists have not offered or developed a consistent approach to evaluating regression as a test for the existence of a common method of proof. One implication of our analysis is that whether regression analysis is useful in the class certification

context goes well beyond whether data are available and whether a regression can be specified to yield a single, non-zero coefficient associated with the collusive behavior at issue. Tests of macro-commonality and micro-commonality provide necessary steps to ensure that a regression analysis constitutes a common method of proof.

How should these tests be implemented? Tests of macro-commonality generally should be performed first, as they provide guidance on the types of micro-commonality tests that will be most helpful. In the absence of a macro-commonality test, micro-commonality tests may become akin to individualized inquiry as the economist will not know which groups of potential class member should be selected for micro-commonality testing. In other words, macro-commonality tests provide guidance on where to conduct micro-commonality tests. For example, if macro-commonality tests were to identify four clearly distinct groups of proposed class members, then micro-commonality tests within each of these groups of class members would be necessary to ensure completeness.

V. The Economics Underlying the Issue of Commonality

As has been demonstrated by the empirical inquiries in Section IV, proof of impact from a regression does not constitute proof of common impact. On the contrary, economic theory and empirical evidence suggest that antitrust violations are likely to result in a range of impacts, from none for some plaintiffs to significant impact for others and thus underscore the importance of the distinguishing between proving impact and proving *common* impact.

While there is no doubt that collusive agreements can yield greater profits for cartel members, Nobel laureate George Stigler demonstrated in *A Theory of Oligopoly* that horizontal agreements are inherently unstable and, as a consequence, are fundamentally different from

competitive equilibria.⁴⁵ Indeed, the same incentives associated with successful horizontal agreement and impact, *i.e.*, the transfer of surplus from customers to sellers, will encourage the horizontal competitors to deviate from the agreement resulting in less than full and consistent impacts or even zero impact.⁴⁶

The deviations from an agreement, either in the form of price or non-price competition, are termed “cheating” in the industrial organization literature. The term – somewhat unfortunate in that it suggests irregularity – simply means competition despite the presence of a horizontal agreement. Where one observes the absence of an effective illegal horizontal agreement, one of the principal reasons is that competitive divergences from any potential agreement, *i.e.*, cheating, make such an agreement unworkable. When horizontal agreements are reached, the empirical evidence is that many of them work intermittently or incompletely.

Success of a horizontal agreement depends in part on the ability of cartel members to deter those who deviate from the agreement. Such deterrence requires monitoring to detect cheating, but also imposing penalties on those who try to gain additional sales through undercutting the collusively agreed-upon price. Unless the penalty can somehow be targeted to impose costs only on the cheater, the imposition of penalties may end the agreement itself. The information problems of cartel enforcement identified by Stigler inspired other work, most notably by Green and Porter (1984), who cast Stigler's problem in the context of repeated games of incomplete information. This literature has produced an extensive list of factors that facilitate

⁴⁵ George J. Stigler, “A Theory of Oligopoly”, 72 *The Journal of Political Economy* (No. 1, Feb. 1964), 44-61.

⁴⁶ Stigler at 46.

a collusive agreement. When these factors are present, cartel members may have limited incentives to deviate from the agreement which will therefore become more stable.⁴⁷

Economic analysis of cartels is a substantial component of the broader literature on oligopoly. The implications of cheating, however, for how regression methods are used in antitrust litigation have not been drawn. In our view, the remedy is straightforward: Rather than view mixes of impact and non-impact as anomalous, the issue of proof of common impact first should be approached with a substantial inquiry into the facts of the case, especially how the alleged horizontal agreement was maintained and enforced. Second, if regression methods are to be used to establish proof of impact on a common, classwide basis, then inquiries should be conducted to determine whether provisional results meet the *macro-* and *micro-commonality* tests proposed here.

VI. Concluding Remarks

Across most U.S. circuit courts there is an emerging consensus encouraging scrutiny of methodologies intended to provide common proof of impact across proposed class members. As courts evaluate the strengths and limitations of regression, it will become more apparent that classwide impact cannot necessarily be established using common proof simply because a regression can be specified. Regression is a useful tool for controlling potentially confounding variables, but whether regression results constitute a common method of proof requires both a well-designed regression and testing of macro and micro-commonality. Data availability, the selection of a benchmark, and other case-specific elements influence the quality of the regression and whether it yields reliable proof.

⁴⁷ Stability can only result in a dynamic setting with imperfect information, as it is only repeated contexts that allow credible threats of punishment, and only imperfect information that gives rise to the possibility of cheating and the importance of monitoring.

Our contribution here concerns the commonality of proof. Which of the two tests that we prescribe is more important? Without proof of micro-commonality, regression analysis generally will not constitute a common method of proof. If micro-commonality can be demonstrated, then proof of macro-commonality increases the likelihood that regression provides a common method of proof for the entire class as opposed to sub-groups of purchasers within the class. Ultimately, testing of micro- and macro-commonality are necessary albeit not sufficient steps to determine whether regression analysis is likely to provide a class-wide proof of impact as it is also necessary to examine other factors including data availability, the existence of a benchmark period and other case-specific elements.

Bibliography

ABA Section of Antitrust Law, *Econometrics: Legal, Practical, and Technical Issues*, 224 (ABA Publishing 2005).

Amchem Products v. Windsor, 521 U.S. 591, 625 (1997).

Aten, Bettina, "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005.

Baker, Jonathan and Daniel Rubinfeld, "Empirical Methods in Antitrust Litigation: Review and Critique," 6 *American Law and Economics Review* 386 (1999).

Blades, et al v. Monsanto Company, et al., 400 F 3d 562 (8th Cir. 2005).

Castano v. Am. Tobacco Co., 84 F.3d 734, 744 (5th Cir. 1996).

Cook, Gregory C., and Charlton A. Rugg, "Tightening Trends in Antitrust Class Certification," *The Antitrust Practitioner* 4 (July 2006).

Cordes & Co. Financial Services v. A.G. Edwards & Sons, Inc., 502 F. 3d (2nd Cir. 2007).

Dukes et al. vs. Wal-Mart, 509 F. 3d 1168 (9th Cir. 2007).

Eisen v. Carlisle & Jacquelin, 417 U.S. 156 (1974).

Fisher, Franklin M., "Multiple Regression in Legal Proceedings," 80 *Columbia Law Review* 702 (1980).

Freeland v. AT&T Corp., 238 F.R.D. 130 (S.D.N.Y. 2006).

General Telephone Company of the Southwest v. Falcon, 457 U.S. 147 (1982).

Green, Edward J., and Robert H. Porter, "Noncooperative Collusion Under Imperfect Price Information," 52 *Econometrica* 1 (1984).

In re Hydrogen Peroxide Antitrust Litig., 552 F 3d 305 (3d Cir. 2008).

In re IPO Sec. Litig., 471 F.3d 24 (2d Cir. 2006).

In re Medical Waste Services Antitrust Litigation (Slip Copy, 2006 WL 538927 (D. Utah)).

In re PolyMedica Corp. Sec's Litig., 432 F.3d (1st Cir. 2005).

In re Universal Serv. Fund Tel. Billing Practices Litig., 219 F.R.D. 661, 678 (D. Kan. 2004).

Page, William. "The Limits of State Indirect Purchaser Suits: Class Certification in the Shadow of Illinois Brick," 67 *ANTITRUST L.J.* 4, 12 (1999-2000).

Piggly Wiggly Clarksville, Inc. v. Interstate Brands Corp., 215 F.R.D. 523 (E.D. Tex. 2003), *aff'd*, 100 Fed. Appx. 296 (5th Cir. 2004).

Simmons, Ian, Alexander P. Okuliar and Nilam A. Sanghvi, "Without Presumptions: Rigorous Analysis in Class Certification Proceedings," *Antitrust* (Summer 2007).

Stigler, George, "A Theory of Oligopoly," *Journal of Political Economy* (1964).

Szabo v. Bridgeport Machines, Inc., 249 F.3d 672 (7th Cir. 2001).

Weisfeld v. Sun Chem. Corp., 210 F.R.D. 136, 143 (D.N.J. 2002), *aff'd* 84 F. App'x 257 (3d Cir. 2004).

Appendix

Recent rulings in the circuit courts are consistent with this emerging consensus with respect to the use of regression. For example:

- **First Circuit** in 2005 wrote in *PolyMedica* that:

[W]hile *Eisen* prohibits a district court from inquiring into whether a plaintiff will prevail on the merits at class certification, it “does not foreclose consideration of the probable course of litigation,” as contemplated by *Falcon* ... a district court must formulate some prediction as to how specific issues will play out in order to determine whether common or individual issues predominate in a given case.⁴⁸

- **Second Circuit** in 2006 ruled in *In re Initial Public Offerings Securities Litigation (IPO)* that:

(i) a district judge may certify a class only after making determinations that each of the Rule 23 requirements has been met;

(ii) such determinations can be made only if the judge resolves factual disputes relevant to each Rule 23 requirement and finds that whatever underlying facts are relevant to a particular Rule 23 requirement have been established and is persuaded to rule, based on the relevant facts and the applicable legal standard, that the requirement is met;

(iii) the obligation to make such determinations is not lessened by overlap between a Rule 23 requirement and a merits issue, even a merits issue that is identical with a Rule 23 requirement;

(iv) in making such determinations, a district judge should not assess any aspect of the merits unrelated to a Rule 23 requirement;

(v) a district judge has ample discretion to circumscribe both the extent of discovery concerning Rule 23 requirements and the extent of a hearing to determine whether such requirements are met in order to assure that a class action certification motion does not become a pretext for a partial trial of the merits.⁴⁹

- **Third Circuit** in 2008 ruled in *In Re Hydrogen Peroxide Antitrust Litigation* that:

Factual determinations supporting Rule 23 findings must be made by a preponderance of the evidence. Second, the court must resolve all factual or legal disputes relevant to class certification, even if they overlap with the merits—including disputes touching on elements of the cause of action. Third, the court’s obligation to consider all relevant evidence and arguments extends to expert testimony, whether offered by a party seeking class certification or by a party opposing it.⁵⁰

⁴⁸ *PolyMedica*, 432 F.3d at 6 (quoting *Waste Management Holdings*, 208 F.3d at 288).

⁴⁹ *IPO*, 471 F.3d at 41.

⁵⁰ *Hydrogen Peroxide*, at 5.

- **Fourth Circuit** in 2005 ruled in *Gariety v. Grant Thornton, LLP* that “by accepting the plaintiffs’ allegations for purposes of certifying a class in this case, the district court failed to comply adequately with the procedural requirements of Rule 23.”⁵¹
- **Fifth Circuit** in 2007 in *Regents of the University of California v. Credit Suisse First Boston (USA), Inc.* condoned a review of facts beyond the pleadings and reversed a class certification order, citing to its own opinions and to *IPO*, *Gariety* and others.⁵²
- **Seventh Circuit** in 2001 wrote in *Szabo v. Bridgeport Machines, Inc.* that “a judge should make whatever factual and legal inquiries are necessary under Rule 23, [even if] the judge must make a preliminary inquiry into the merits.”⁵³
- **Eighth Circuit** in 2005 wrote in *Blades v. Monsanto* that “in ruling on class certification, a court may be required to resolve disputes concerning the factual setting of the case, [including] the resolution of expert disputes concerning the import of evidence.”⁵⁴
- **Ninth Circuit** in 2007 wrote in *Dukes et al. vs. Wal-Mart* that “courts are not only ‘at liberty to’ but *must* ‘consider evidence which goes to the requirements of Rule 23 even [if] the evidence may also relate to the underlying merits of the case.’”⁵⁵
- **Ten Circuit** in *In re Medical Waste Services Antitrust Litigation* the district court wrote that plaintiffs would have to prove their case through “an exhaustive market-by-market, customer-by-customer, product-by-product, time period-by-time period inquiry” and criticized plaintiffs’ expert for presuming antitrust impact rather than offering a method for demonstrating it.⁵⁶

⁵¹ Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” *Antitrust*, Summer 2007, footnote 54.

⁵² Ian Simmons, Alexander P. Okuliar and Nilam A. Sanghvi, “Without Presumptions: Rigorous Analysis in Class Certification Proceedings,” *Antitrust*, Summer 2007, footnote 55.

⁵³ *Szabo v. Bridgeport Machines, Inc.*, 249 F.3d 672 (7th Cir. 2001).

⁵⁴ *Blades, et al v. Monsanto Company, et al.*, 400 F 3d 562 (8th Cir. 2005).

⁵⁵ *Dukes v. Wal-Mart*, 509 F.3d 1168, 1177 n.2 (9th Cir. 2007) (quoting *Hanon v. Dataproducts Corp.*, 976 F.2d 497, 509 (9th Cir. 1992)).

⁵⁶ Gregory C. Cook and Charlton A. Rugg, “Tightening Trends in Antitrust Class Certification,” *The Antitrust Practitioner*, p.3.

Table 1. Plaintiff-Style Regression Estimate of Alleged Overcharge

	(1)	(2)	(3)
Overcharge	1.10** (0.20)	-0.12 (0.27)	2.64** (0.32)
Observations	5185	2632	3775
R ²	0.79	0.80	0.81

Notes:

[1] Standard errors are in parentheses.

[2] ** p<0.01, * p<0.05

[3] The dependent variable is the average price per liter by product specification, location, store type, and half-year. The price per liter is adjusted to exclude state sales and excise taxes using tax data from www.taxadmin.org. The price per liter is also adjusted to reflect cross-location differences in food price levels using data from the B.E.A. working paper "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005, p.12.

[4] Results in column (1) correspond to a specification in which the variable "Overcharge" equals 1 for Tampa, New York, Denver, Miami, and Boston, and 0 for Atlanta, Chicago, Kansas, Minneapolis, Los Angeles, San Diego and San Francisco.

[5] Results in column (2) correspond to a specification in which the variable "Overcharge" equals 1 for Tampa, New York, Denver, Miami, and Boston, and 0 for Atlanta, Kansas, and San Diego.

[6] Results in column (3) correspond to a specification in which the variable "Overcharge" equals 1 for Tampa, New York, Denver, Miami, and Boston, and 0 for Chicago, Minneapolis, Los Angeles and San Francisco.

[7] Regressions also controlled for store type (drug store, discount sample store, hispanic market, and liquor store), brand (Castillo, Captain Morgan, Malibu, Bacardi, Myers's, and RonRico), rum type (dark, flavored, gold, light, Proof 151), container size (375 ml, 750 ml, 1000 ml, 1750 ml) and year (1996, 1997, 1998, 1999, 2000).

Table 2. City-Specific Regression Estimates of Alleged Overcharge

	(1)
Overcharge - Tampa	3.47** (0.30)
Overcharge - New York	-0.99** (0.30)
Overcharge - Denver	1.36** (0.30)
Overcharge - Miami	0.98** (0.30)
Overcharge - Boston	0.71* (0.30)
Observations	5185
R ²	0.83

Notes:

[1] Standard errors are in parentheses.

[2] ** $p < 0.01$, * $p < 0.05$

[3] The dependent variable is the average price per liter by product specification, location, store type, and half-year. The price per liter is adjusted to exclude state sales and excise taxes using tax data from www.taxadmin.org. The price per liter is also adjusted to reflect cross-location differences in food price levels using data from the B.E.A. working paper "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005, p.12.

[4] Results correspond to a specification in which the benchmark markets are Atlanta, Kansas, San Diego, San Francisco, Chicago, Los Angeles and Minneapolis.

[5] Regressions also controlled for store type (drug store, discount sample store, hispanic market, and liquoru store), brand (Castillo, Captain Morgan, Malibu, Bacardi, Myers's, and RonRico), rum type (dark, flavored, gold, light, Proof 151), container size (375 ml, 750 ml, 1000 ml, 1750 ml) and year (1996, 1997, 1998, 1999, 2000).

Table 3. Brand and City-Specific Regression Estimates of Alleged Overcharge

	(1)	(2)	(3)	(4)	(5)	(6)
	Bacardi Only	Castillo Only	Captain Morgan Only	Malibu Only	Myers's Only	RonRico Only
Overcharge - Tampa	3.88** (0.43)	1.89** (0.56)	4.07** (0.84)	2.95** (0.72)	4.48** (1.34)	1.82** (0.52)
Overcharge - New York	-1.37** (0.43)	-0.21 (0.47)	-0.30 (0.92)	-1.22 (0.71)	-0.56 (1.33)	-0.41 (0.52)
Overcharge - Denver	1.40** (0.43)	1.13* (0.47)	2.53** (0.84)	1.87** (0.71)	-0.35 (1.33)	0.55 (0.52)
Overcharge - Miami	1.20** (0.43)	0.22 (0.47)	1.44 (0.84)	1.18 (0.71)	0.83 (1.33)	0.45 (0.52)
Overcharge - Boston	0.56 (0.43)	1.07* (0.47)	1.61 (0.84)	1.07 (0.71)	0.55 (1.33)	-0.26 (0.52)
Observations	2663	594	607	492	341	488
R ²	0.82	0.60	0.79	0.78	0.74	0.78

Notes:

[1] Standard errors are in parentheses.

[2] ** p<0.01, * p<0.05

[3] The dependent variable is the average price per liter by product specification, location, store type, and half-year. The price per liter is adjusted to exclude state sales and excise taxes using tax data from www.taxadmin.org. The price per liter is also adjusted to reflect cross-location differences in food price levels using data from the B.E.A. working paper "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005, p.12.

[4] Results correspond to a specification in which the benchmark markets are Atlanta, Kansas, San Diego, San Francisco, Chicago, Los Angeles and Minneapolis.

[5] Regressions also controlled for store type (drug store, discount sample store, hispanic market, and liquor store), brand (Castillo, Captain Morgan, Malibu, Bacardi, Myers's, and RonRico), rum type (dark, flavored, gold, light, Proof 151), container size (375 ml, 750 ml, 1000 ml, 1750 ml) and year (1996, 1997, 1998, 1999, 2000).

Table 4. City and Year-Specific Regression Estimates of Alleged Overcharge of Castillo Brand Rum

	(1)	(2)	(3)	(4)	(5)
	1996	1997	1998	1999	2000
Overcharge - Tampa	0.00 (0.00)	2.38* (1.05)	1.74* (0.73)	2.15** (0.73)	1.77** (0.58)
Overcharge - New York	-0.12 (0.54)	0.01 (0.78)	-0.17 (0.66)	-0.24 (0.55)	-0.47 (0.44)
Overcharge - Denver	1.64** (0.54)	1.34 (0.78)	1.03 (0.66)	1.03 (0.55)	0.69 (0.44)
Overcharge - Miami	0.18 (0.54)	0.44 (0.78)	0.20 (0.66)	0.25 (0.55)	0.13 (0.44)
Overcharge - Boston	1.38** (0.54)	1.49 (0.78)	1.20 (0.66)	0.87 (0.55)	0.50 (0.44)
Observations	109	120	128	119	118
R ²	0.76	0.52	0.59	0.62	0.70

Notes:

[1] Standard errors are in parentheses.

[2] ** p<0.01, * p<0.05

[3] The dependent variable is the average price per liter by product specification, location, store type, and half-year. The price per liter is adjusted to exclude state sales and excise taxes using tax data from www.taxadmin.org. The price per liter is also adjusted to reflect cross-location differences in food price levels using data from the B.E.A. working paper "Report on Interarea Price Levels," *Bureau of Economic Research*, WP 2005-11, November 30, 2005, p.12.

[4] Results correspond to a specification in which the benchmark markets are Atlanta, Kansas, San Diego, San Francisco, Chicago, Los Angeles and Minneapolis.

[5] Regressions also controlled for store type (drug store, discount sample store, hispanic market, and liquor store), brand (Castillo, Captain Morgan, Malibu, Bacardi, Myers's, and RonRico), rum type (dark, flavored, gold, light, Proof 151), container size (375 ml, 750 ml, 1000 ml, 1750 ml) and year (1996, 1997, 1998, 1999, 2000).

Table 5. Transactional Data Before and After Price Announcements

	Invoice Date	Invoice Price	Customer	Seller	Product	Before/After Effective Date of Price Increase
1	06/11/98	\$1.29	C-1	S-1	Product 1A	0
2	07/30/98	\$1.29	C-1	S-1	Product 1A	0
3	12/17/98	\$1.29	C-1	S-1	Product 1A	0
4	03/18/99	\$1.34	C-1	S-1	Product 1A	1
5	09/17/99	\$1.34	C-1	S-1	Product 1A	1
6	09/29/98	\$0.90	C-2	S-2	Product 2A	0
7	12/31/98	\$0.90	C-2	S-2	Product 2A	0
8	02/26/99	\$0.90	C-2	S-2	Product 2A	0
9	03/31/99	\$0.90	C-2	S-2	Product 2A	1
10	09/30/99	\$0.90	C-2	S-2	Product 2A	1
11	08/31/98	\$0.90	C-3	S-3	Product 3	0
12	12/31/98	\$0.90	C-3	S-3	Product 3	0
13	07/02/99	\$0.91	C-3	S-3	Product 3	1
14	10/06/99	\$0.91	C-3	S-3	Product 3	1
15	12/07/99	\$0.91	C-3	S-3	Product 3	1
16	07/17/98	\$1.29	C-4	S-1	Product 1B	0
17	08/12/98	\$1.29	C-4	S-1	Product 1B	0
18	11/11/98	\$1.29	C-4	S-1	Product 1B	0
19	06/10/99	\$1.29	C-4	S-1	Product 1B	1
20	06/25/99	\$1.29	C-4	S-1	Product 1B	1
21	08/28/99	\$1.06	C-5	S-4	Product 4	0
22	12/07/98	\$1.06	C-5	S-4	Product 4	0
23	02/25/99	\$1.11	C-5	S-4	Product 4	1
24	04/14/99	\$1.11	C-5	S-4	Product 4	1
25	12/17/99	\$1.11	C-5	S-4	Product 4	1
26	04/22/98	\$1.19	C-6	S-2	Product 2B	0
27	11/16/98	\$1.19	C-6	S-2	Product 2B	0
28	10/27/99	\$1.21	C-6	S-2	Product 2B	1
29	04/22/99	\$1.21	C-6	S-2	Product 2B	1
30	06/21/99	\$1.21	C-6	S-2	Product 2B	1

Table 6. Regression Analysis of the Impact of the Price Announcements

	(1)
(After) Price Announcement	0.0217** (0.0044)
C-2	-0.1856** (0.0075)
C-3	-0.1840** (0.0074)
C-4	0.2243** (0.0075)
C-5	0.2043** (0.0075)
C-6	0.1120** (0.0075)
Constant	1.0770** (0.0059)
Observations	30
Adjusted R ²	0.995

Notes:

[1] Standard errors are in parentheses.

[2] ** p<0.01.

DC1:799634.2