Inducing Greater Transparency: Towards the Establishment of Ethical Rules for Econometrics

David M. Levy
Buchanan Center
George Mason University
Fairfax VA 22030
DavidMLevy@aol.com

Sandra J. Peart
Economics Department
Baldwin-Wallace College
Berea OH 44017
speart@bw.edu

October 11, 2005

An earlier version of the paper was presented at the 2003 Joint Statistical Meetings and the George Mason Summer Institute for the Preservation of the History of Economics in Economics. We have benefitted from the comments of William Seltzer and Margo Anderson and, especially, this journal's referee. The paper began with a conversation between Levy and Paul David at the Economics of Science conference at Notre Dame in April 1997 and was greatly stimulated by Perci Diaconis's as yet unpublished 1998 IMS lecture. Preliminary versions were presented at the George Washington University Economics Seminar, the 1999 Canadian Law and Economics Association meetings, the George Mason Statistics Department Seminar and the University of Alberta Econometrics Seminar. We have benefitted from comments from James Buchanan, Adolf Buse, Roger Congleton, Tyler Cowen, Mark Crain, Don Gantz, Jim Gentle, Bruce Kobayashi, David Meiselman, John Miller, David Ribar, Robert Tollison and other participants. The command files to replicate the monte carlo study are available upon request.

Forthcoming: *Eastern Economic Journal*

1 Introduction

This paper begins with a historical puzzle. We wonder why econometrics has no code of professional ethics, whereas there are well-developed codes of ethics for statistical communities such as the American Statistical Association. The historical experience, which we review briefly in Section 2, is that professional ethics in statistics grew out of "statistical consulting." To the extent that econometricians engage in similar sorts of economic statistical consulting, they might also benefit from a professional code of ethics that, as a minimum, induces greater transparency.

In order further to motivate this argument, section 2 presents a simple model of the trade off that exists in econometric estimation between bias and efficiency. An econometrician, who is sympathetic with the client's preferences over estimates, may choose selectively to report the estimate. In Section 3, we consider an example of non-transparent econometric estimation in some detail. We examine whether such non-transparency might be eliminated by market forces, in particular, by competition among econometric experts and we show that competition fails to substitute for ethical constraints even in what may be the most favorable case for the competitive model. Finally, section 4 proposes a mechanism to induce greater transparency in econometric estimation: a bootstrapping rule that makes transparency the minimax solution for the expert.

2 The "Human Element" in Statistical Consulting

The fact is that there are widely-discussed codes of ethics in statistical associations, such as the International Statistical Institute (1985) and the American Statistical Association (2000), but nothing like these in econometrics.[1] Why is this so? Statistical ethics arose in the process of a trading

[1] Gorlin (1999), an 1100 page compendium of "codes of professional responsibility," indexes professions alphabetically. The list refers to: chiropractic (1067), computing (1068), counseling (1070), dental hygiene (1073), dentistry (1074), direct marketing (1076), dispute resolution (1078), and engineering (1079).

relationship, an explicit exchange referred to as "statistical consulting," in which the statistician trades expertise with a "client" for some other good thing, be it material income or co-authorship on a research project. Within the exchange setting, an explicit code of statistical ethics attempts to make clear to the client what is and what is not part of the bargain. So, the American Statistical Association's "Ethical Guidelines" contains sections on the statistician's "responsibilities" to "Funders, Clients, and Employers"; "Research Subjects"; and "Other Statisticians or Statistical Practitioners" (ASA 2000, pp. 6, 7, 8-9).

For statisticians, "client" is a very general term:

> The word client will denote the man or group of people who will use the results of the study. Or, the same word may denote an expert or group of experts in substantive fields ... who are responsible to the man who will pay the bill for the study. Deming (1965, pp. 1883-84)

Exchanges for money are no different than exchange for co-authorship:

> The same principles apply also to the statistician who works as a member of a research team. (Deming, 1965, p. 1884).

In the discussion that led up to the 2000 ASA Code of Professional Ethics, here is how John Gardener described Edward Deming's practice as a statistical consultant:

> Statisticians proudly claim "Ed" Deming as one of our heroes. He helped revolutionize industrial quality and productivity. He was also a stickler for the ethical practice of statistics. Among items featured in his personal code of conduct, which are not found in other statistical ethics sources:
> Devote oneself to the statistics profession alone.
> Set ethical rules with the client up front.
> Limit own role as statistician only to those functions supported by statistical theory.
> Draw conclusions only about the frame, not the population.
> Retain exclusive publication control over statistical matter one reports.
> Assure reports clearly state who did what in conducting the study and document all meaningful possible sources of error.
> Prepare own expert testimony. (Lawyer can help clarify, but not originate, positions.)
> Reserve right to break off an engagement without explanation. Do so if a client or colleague (on a joint study) does unacceptable work.
> Retain all rights to statistical theory developed on an assignment to share them with the profession. (Gardiner 1996)

Deming himself made it clear that the statistical consultant qua professional statistician had no interest in the substantive questions that interested his employer (Deming 1965).

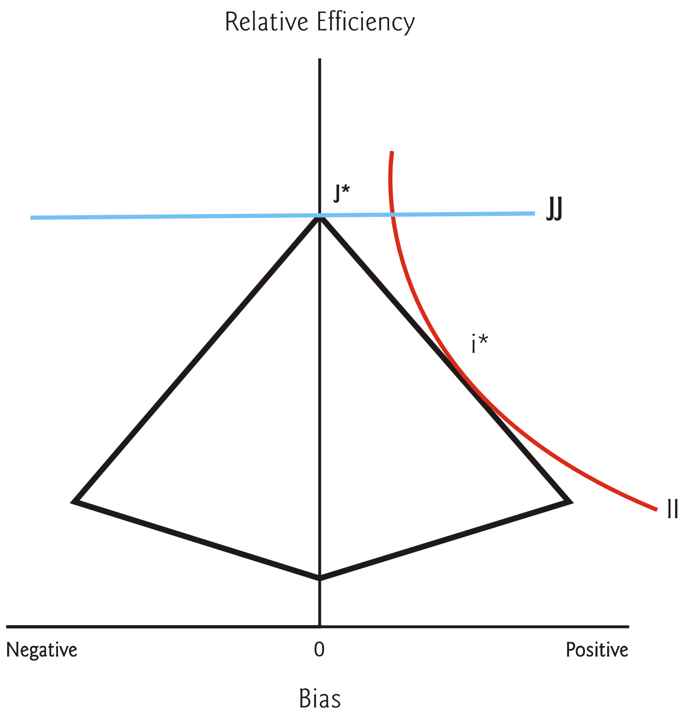
In an important article in *American Statistician*, Stephen Vardeman and Max Morris suggest that the "human element" in statistics arises from the fact that all-too-often the client has decided preferences over outcomes. We find the crux of the matter in their advice to the young statistician, emphasized below:

> If your assignment is to help with statistical consulting, you are already wrestling (at a "trainee" level) with some of the serious issues faced by one segment of our profession. Carefully consider and handle these now, as you begin to see how the "human element" of statistical consulting requires thoughtful and principled discipline. You're going to have to argue with yourself in conversations like: -
>
> What looks to me like the thing that should be done would take two hours to explain and several more hours of my time to implement, while this client would be happy with something less appropriate that I could explain in five minutes …
>
> *-This client really wants "A" to be true, but these data look inconclusive …*
>
> -This looks pretty much OK except for that oddity over there that the client doesn't really want to discuss. Vardeman and Morris (2003, p. 23)

The "human element" in Varderman and Morris is akin to a form of sympathy that is so important in face-to-face negotiations.[2]

The question we focus on here, is what are "wants"? In Figure 1, we present the ethical problem of statistical consulting as one of competing preferences over estimates where we model the trade-off between bias and statistical efficiency. We depart from the textbook treatment of the goals of statistical research and allow bias to be a desired property of an estimate. The constraint we imagine follows the simple mechanics of specification search or data mining where one makes many estimates and picks one's favorite (Learmer 1983, Denton 1985). In particular, these constraints, the

[2]We have developed a technical working definition of sympathy in Levy-Peart 2005. For our purposes here, it is sufficient to suggest that a researcher who is sympathetic with his client's preferences over estimates, may be induced to choose and then offer the client an estimate that the client would want to obtain. Reading Gardiner's description of Deming's practice one can visualize the ideal expert-client relationship as that in a dictator game. With sympathetic agents, however, sharing results even in dictator games. See Camerer and Thaler (1995), Hoffman, McCabe, Smith (1996, 1999), Sally (2001)



Competing Rational Estimates

replication sets, drawn from Feigenbaum-Levy 1996, result from computing a number of unbiased estimates and mapping out the frontier combination of bias and efficiency.[3]

We consider two sorts of preferences – one for a statistician behind a veil of ignorance, and one for a client. Following Deming, before he meets the client the statistician is interested only in statistical efficiency. Either the statistician does not care about the value of the parameter to be estimated (Deming's position), or perhaps he does care but is unwilling to give up any amount of statistical efficiency to get a more pleasing estimate. In Figure 1, this possibility is described by indifference curve JJ.[4] Thus for a statistician the rational estimate is j*. The client, however, has indifference curves of the shape marked by II and is thus willing to trade away some statistical efficiency for some gain in bias. For the client, the rational estimate is i*. Our point is that in the absence of ethical constraints or other transparency-inducing institutional arrangements, the client may be able to induce the sympathetic researcher to produce the estimate i*.

---

[3]Rational choice estimation is the "evil twin" of exploratory data analysis [EDA]. Whereas EDA supposes that a model changes as one's beliefs move to encompass more of what is true (Levy 1999/2000), rational choice estimation starts with a true model and finds what is profitable to believe.

[4]If the preferences are lexicographical then J is to be viewed as a pseudo-indifference curve and is marked with pseudo-Roman numbers.

3 Is Transparency Incentive Compatible?

In large measure to help counter such an outcome, ASA and other codes of ethics for statistical research place a heavy emphasis on transparency, a minimal requirement for the ethical choice of statistical estimates.[5] Before turning to transparency in some detail, we ask an additional question, one long familiar in economics. Does competition result in an efficient outcome regardless of the motivation of the statistical researchers? If so, then econometric researchers for hire might be said to act *as if* we were ethical regardless of individual motivation.

To answer this question, we consider the case when a client hires a sympathetic statistician, someone who comes to see the world the way the client would like him to see the world. The question we ask is whether competition is sufficient to induce what is arguably the weakest of scientific ethical standards, that of transparency.[6] Can competition substitute for personal discipline, ethics, and induce transparency?

The American legal system seems an ideal case to consider such rational choice estimation in a competitive context because the motivation for non-transparencies is all-too-obvious. The case of the expert witnesses seemed to be much on Deming's mind as we learned from Gardiner's report above. Here, we ask whether an institutional reform akin to final-offer arbitration might make transparency incentive-compatible. The condition of incentive-compatibility we employ is that of

---

[5]See notes 2, 5, 8 and 10 on p 5, note 6 on p 6, notes 2, 5 6, 7, 8, 9, 12, 13, 14 on p. 7 of ASA 2000.

[6]We do not pretend that transparency is sufficient for ethical behavior in this context. It leaves aside a wide range of issues, relating to experimentation and ethics, that provided the impetus for Human Subjects Review Boards [HSRB]. Although we largely leave aside these issues here, we note that there is an informal set of procedures dealing with them in experimental economics. See Houser, 2005.

minimax loss.[7]

In this context, the problem is that contending clients hire expert econometricians to press their case before a jury. We suppose that both clients are motivated by a desire to report an efficient estimate and they can find sympathetic econometricians whose preferences come to mirror their own. We do not need to assume that experts are persuaded to pick an estimate in order to earn financial rewards, but only that sympathy will induce them to share. Here, the goods to be shared are the properties of the reported estimates.

We have described the rational choice estimator b of a parameter β, employed by a statistician s. We suppose that s's understanding of the first moment of b is $E(b)^s$. The estimate is *transparent* if for an arbitrary reader t, $E(b)^s = E(b)^t \; \forall t$ and non-transparent when the equality fails.[8] The definition can be generalized to an arbitrary moment. If moments do not exist, transparency is attained if both the writer and reader understand the failure of absolute convergence. A transparent estimate can be biased without raising ethical questions.[9] Transparency is thus intimately related to the ethical property of impartiality as a rule. A judgment is said to be impartial if it is applied without regard to personal identity.

Structural equation estimation is a natural test ground for thinking about non-transparency because the identifying restrictions flow from theoretical insight. It is perhaps not a coincidence that

---

[7]The relationship between expected utility and minimax decision theory is subtle. Savage's contribution to the Princeton Robustness study, the estimator LJS, is a minimax estimator varying a theme due to P. J. Huber, Andrews, *et al.* (1972, p. 2C3). On Huber's original paper, see Savage (1972, p. 291): "An important nonpersonalistic advance in the central problem of statistical robustness."

[8]So defined non-transparency is a case of asymmetric information (Akerlof 1970).

[9]In the discussions leading up to the American Statistical Association (2000), great care was taken to distinguish an estimate in which the bias is transparent, as defended by Bayesians, from an estimate in which the bias is not transparent.

structural equation estimation is also fertile ground study for non-transparent estimation because current conventions do not require the researcher to document the consequences of different selections of instrumental variables.

Consider a demand and supply system (*D & S*) of the following structure:[10]

$$\text{Quantity} = \beta_1 + \beta_2 \text{ Price} + \beta_3 \text{ Income} + \eta \qquad \text{(D)}$$

$$\text{Price} = \alpha_1 + \alpha_2 \text{Quantity} + \alpha_3 \text{ Cost} + \alpha_4 \text{ Weather} + \alpha_5 \text{ Politics} + \varepsilon \quad \text{(S)}$$

We suppose that the client has preferences over the estimated value of β_2. A researcher is required by convention to report only *D,* mentioning *S* casually. Thus, one can choose whether to include one, two or three exogenous variables from *S*. The rational choice estimate is the result of computing all possible combinations which identify a system and then picking.[11] As above, we suppose the client and the sympathetic expert wants both bias and statistical efficiency. We measure the efficiency of estimator *i* by the minimum mean square error [MSE*] of the estimates considered relative to the MSE of estimator *i*; thus, MSE^*/MSE_i.

A simulation is provided to give some idea of the ease with which biased estimates can be generated by such a selection procedure. There are several technical details. First, what is the distribution of the exogenous variables? If they are omitted not only do they change the error distribution but also the degree of over-identification, which changes dramatically the property of 2SLS estimates, Phillips (1983). In the first case considered, all exogenous variables are assumed to be a standard normal. Thus, omitting an exogenous variable in search of a pleasing outcome will not change the normality of the resulting errors.

We consider two types of search. First, there is an unconstrained search for the maximum

---

[10]The alphas are all 1; β_1 is 10; β_2 is -1; β_3 is 3.

[11]This idea results from a conversation with Paul David.

(minimum) value of the estimates of β_2. In the Tables below this is called "Max" and "Min." Second, there is a search which is constrained by the desire to have at least two exogenous variables in the supply curve. These are called "C Max" and "C Min." This will suggest how much the researcher might be willing to give up in efficiency to get bias. 100,000 experiments for N=25, 100, 400, 1600 are performed in *Shazam 8.0*, White (1997).

All of the simultaneous estimates are replicable "two-stage least squares" estimates or as "inefficient two-stage least squares" although only 2SLS and OLS are transparent. The divergence between the "rational choice" estimate and the transparent 2SLS estimate can be thought of as transparency bias. Such bias persists through the case of N=1600.[12]

Table 1: Normal Exogenous Variables
100,000 Replications

	N=25		N=100		N=400		N=1600	
	Bias	Efficiency	Bias	Efficiency	Bias	Efficiency	Bias	Efficiency
OLS	0.40	0.35	0.40	0.08	0.40	0.02	0.40	0.02
2SLS	0.03	1.00	0.01	1.00	0.00	1.00	0.00	1.00
C Min	-0.21	0.27	-0.09	0.48	-0.04	0.54	-0.02	0.54
C Max	0.17	0.58	0.08	0.66	0.04	0.63	0.02	0.63
Min	-1.74	0.00	-0.22	0.14	-0.09	0.21	-0.04	0.21
Max	1.87	0.00	0.16	0.32	0.08	0.30	0.04	0.30

While the bias declines in absolute value as N increases, the reduction in bias from increasing

[12] Judging from 10,000 experiments the bias persists through N=6400. If the bias were measured in terms of the median of the estimates instead of the mean, it too would persist. The experiments were repeated with all exogenous variables following a uniform distribution between 0 and 1. Since it is not surprising that the amount of the bias is acutely sensitive to the distribution of the omitted exogenous variables, these results are not reported.

N by a factor of four can be held in check by moving from the C-max (C-min) to Max (Min). This suggests that the problem of convergence will depend upon how the possible models increase as N increases. The simulation considered only exogenously variables which were truly included in the structure. We leave the problem of identifying the system by employing random numbers for future research. The problem of "pseudo-identification" raises theoretical questions that emerged at the dawn of simultaneous equation estimation and seems to have re-appeared in a new guise.[13]

Literature on the economics of expert witnesses has supposed that the jury decision will be made on the basis of an average of such biased estimates. The conclusion of Froeb and Kobayashi (1996) for the case of biased experts before a jury, is that the average of their estimates will be unbiased. In this, they are followed by Posner who contends that this property of a competitive procedure makes the idea of a court-appointed expert witness unwarranted:

> The use of a court-appointed expert is problematic when (for example, in the damages phase of the case) the expert witness's bottom line is a number. For then, in the case of opposing witnesses, the trier of fact can "split the difference," after weighting each witness's estimate by its plausibility. Posner (1999, p. 1539)

And, it will be obvious from the tables above that, roughly speaking, the policy determined by the average of Min and Max or by the average of C-Min and C-Max will be unbiased.

However, this policy will have a higher variance than a policy determined by both using 2SLS. Thus, we create the familiar prisoner's dilemma in statistical context. While it is in the interest of each statistician considered separately to engage in selective under-reporting of results, it is in the interest of the statisticians considered as a group not to under-report. This is shown by the result that the

[13] We have benefitted from a conversation with Arthur Goldberger about the concerns of the Cowles Commission on pseudo-identification of structural equation estimates and with Adolf Buse on the modern discussion of weak-identification.

diagonal element is roughly unbiased but the cell where both statisticians engage in "bias seeking" behavior has lower statistical efficiency than when they restrain themselves.

As an illustration of the point, a simulation of a quarter million replications was conducted to generate the statistician's dilemma using the case of normal exogenous variables with N=400. Here bias is computed in terms of deviation from the 2SLS estimate so as to represent the transparency bias. The efficiency is now the mean square error relative to the minimum where bias is measured in terms of deviation from the mean 2SLS estimate.

Table 2: Econometrician's Dilemma
Normal Exogenous Variables, N=400
250,000 Replications

	2SLS		C-Min		Min	
	Bias	Efficiency	Bias	Efficiency	Bias	Efficiency
2SLS	0.00	1.00	-0.02	0.81	-0.05	0.50
C-Max	0.02	0.88	0.00	0.97	-0.03	0.73
Max	0.04	0.64	0.02	0.92	-0.01	0.86

The optimistic conclusion of Froeb and Kobayashi (1996), followed by Posner (1999), depends upon their exclusive focus on the problem of bias. But if variance is also an issue because one worries about the efficiency of the process then their optimism about the unrestricted competitive process of expert witness seems more complicated than they suggest. A rule which constrains experts to report only 2SLS results would have a smaller variance than the competitive process modeled above.

In particular, one of Posner's arguments – the better financed expert gathers more evidence [14] – does not consider how the better financed expert might be sufficiently motivated to move from the diagonal C-Min/C-Max to (say) C-Min/Max. The small private gain in bias – this of course is an artifact of the parametric set – comes at an efficiency loss.

4 Making Transparency Incentive Compatible

Let us reflect upon the challenge posed by Judge Posner. Just what might a court-appointed expert witness, (see Tullock 1980), do to improve upon a competitive outcome? Here we consider a statistical variation upon the widely-discussed principle of final-offer arbitration (Crawford 1979, Ashenfelter & Bloom 1984, Ashenfelter, *et al.* 1992) in which the court expert is only allowed to recommend one model, not to propose a compromise between models.[15]

It would be inappropriate to assume that the court-appointed expert has a different motivation from the experts hired by the contending parties. As a consultant, however, she gets paid only for reduction in variance, not for the increase in bias. Can this be accomplished without supposing the court expert to be more knowledgeable than the parties' experts? Can the court expert provide a rule which changes the incentives of the parties' experts?

The *rule* we propose to induce transparency is this: the court-appointed expert takes each of the contending models and bootstraps them. The winning model has the smaller bootstrap

[14]Posner (1999, p. 1488): "Because trial lawyers are compensated directly or indirectly on the basis of success at trial, their incentives to develop evidence favorable to their client and to find the flaws in the opponent's evidence is very great and, if it is a big money case, their resources for obtaining and contesting evidence will be ample."

[15]This idea was suggested by John Miller.

variance.[16] Unlike the general case of final-offer arbitration, in which the judgment depends upon the preferences of the arbitrator, we suppose that the rule can be common knowledge.

Will this rule make transparent estimation a minimax strategy? First, we look at the asymptotic problem and, second, the finite sample problem. Not surprisingly, the former is easier than the latter.

Asymptotics. Bootstrap standard errors of 2SLS are consistent in the *D & S* context we have supposed (Freedman 1984). Therefore if one expert proposes an inefficient 2SLS estimate then the other expert who proposes the efficient 2SLS estimate will by our rule prevail because the bootstrap standard errors, as consistent estimates of the standard error, will reveal which of the competing estimates is more efficient. Transparency thus bounds the loss at 2SLS. Transparency is safe. If one expert proposed a biased, and therefore inefficient estimate, he would risk his opponent producing a biased but somewhat less inefficient estimate. Any report other than transparency risks a larger loss. Non-transparency is not safe. The reporting of the transparent 2SLS estimate therefore minimizes one's maximum loss. The results of Freedman 1984 made into a *rule* and applied to our *D & S* estimation thus **prove:**

Theorem. The *rule* makes transparent estimation is minimax in the *D & S* estimation situation considered.

Finite samples. Freedman (1984) gives reason for optimism for the application of bootstrap in the finite sample case. We return to the *D & S* context above. In our setup, as one moves from 2SLS to C-Min/C-Max and then to Min/Max the number of identifying restrictions falls; hence, the

[16]An alternative rule might be to define a range in which the models are equally acceptable. Presumably the "splitting the difference" rule would then prevail.

number of existing moments falls. As the bootstrap estimate of variance is not a robust technique, and thus sensitive to tail mass, as the moments vanish, the tail mass increases. Thus the estimated value of the 2SLS estimates will be predictably lower than the bootstrap variance of C-Min/C-Max which in turn will be predictably lower than the bootstrap variance of Min/Max. When the number of existing moments is the same, the results are not so obvious. If C-Min competes with C-Max then C-Min has probability P of prevailing. If Min competes with Max then Min has probability Q of prevailing. There is no reason to believe that either $P=1-P$ or $Q=1-Q$.

Would making the decision on the basis of the bootstrap variance introduce transparency in the game of expert witness? Unlike the general problem of final-offer arbitration where the knowledge of the arbitrator's preferences is problematic, here the decision rule of the court expert can be taken as common knowledge.[17] Could the court now see which of the two estimates is associated with the smaller variance? The game of expert witness now that pictured in Figure 2. The first column presents the three possible choice made by the advocates of "high" side. The second column presents the three possible choices made by the advocates of "low" side. The third column is the outcome which results for each pair of plays. If *either* player prefers the certainty of 2SLS to the gamble associated with reporting C-Min/C-Max or Min/Max then for that player, reporting 2SLS is a minimax loss strategy. This result is consistent with what is known about final-offer arbitration in general: there is safety in being reasonable.[18]

[17]Ashenfelter and Bloom (1984, p. 112) point out how the conclusions in Crawford (1979) depend critically upon this assumption.

[18]Ashenfelter, *et al.* (1992, p. 1427): " ... risk averse bargainers can mitigate the risks inherent in FOA [final-offer arbitration] by submitting more reasonable offers while CA [conventional arbitration] offers less scope for mitigation of risk. One way to interpret the conventional wisdom that FOA is riskier than CA is that, by preventing the arbitrator from compromising, the middle of the distribution of

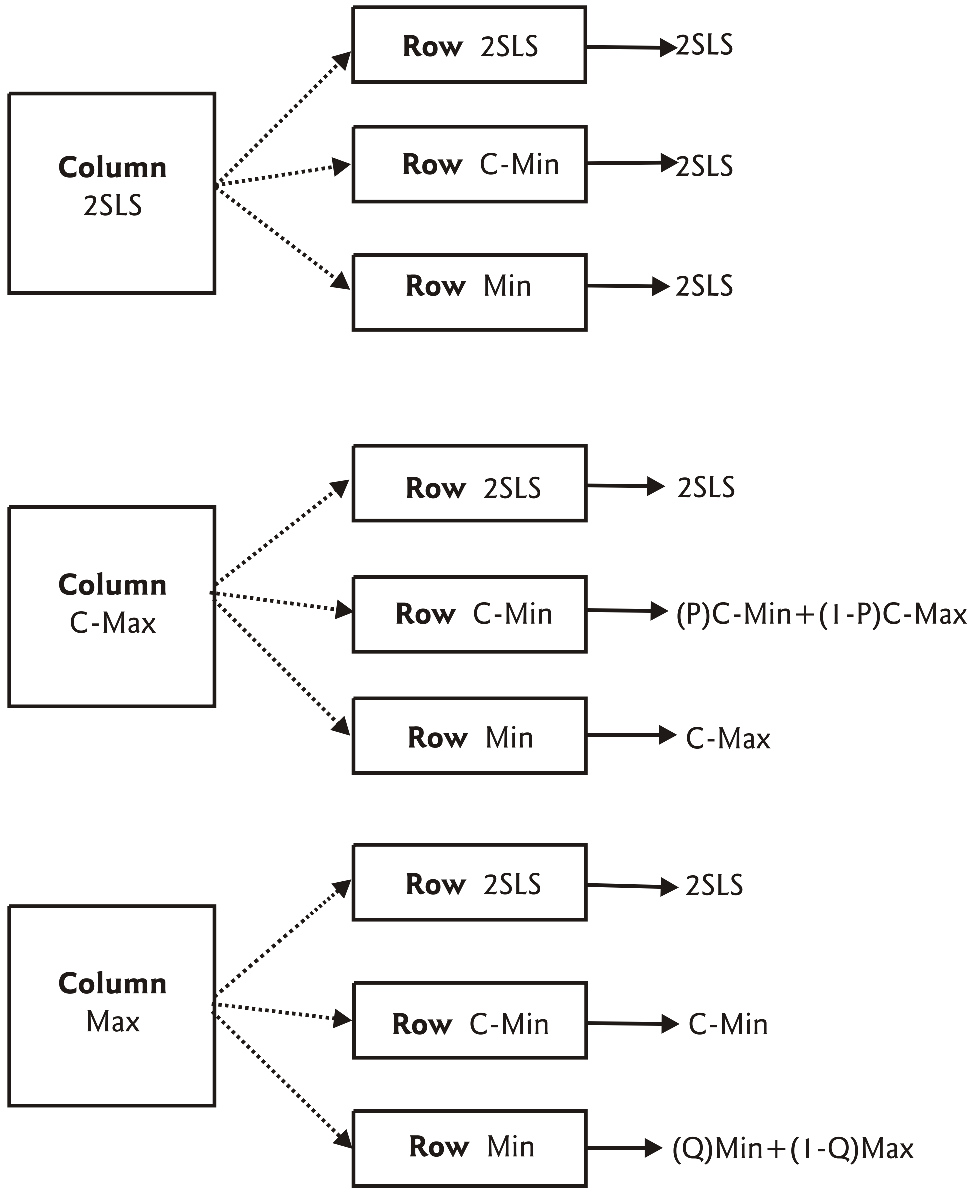


Figure 2. Induced Transparency

---

arbitrator's preferred outcomes is eliminated as potential arbitration awards. This by itself would increase risk. However, FOA also eliminates the tails of the distribution, and this decreases risk."

In the case of N=400, 10K replications, the game in Figure 2 was simulated. The cells in the game on each of the 10K replications was filled in by which of the two contending estimates had the smallest bootstrap standard error. In this case, as could be predicted from Table 1 and Figure 2, the side preferring small numbers can only improve upon 2SLS when it plays C-Min and the other plays Max. For this side 2SLS is minimax. And this suffices to induce transparency.

Table 3: Induced Transparency by Minimizing Bootstrap Variance Normal Exogenous Variables, N=400 10,000 Replications

	2SLS		C-Min		Min	
	Bias	Efficiency	Bias	Efficiency	Bias	Efficiency
2SLS	0.00	1.00	0.00	1.00	0.00	1.00
C-Max	0.00	1.00	0.03	0.64	0.04	0.64
Max	0.00	1.00	-0.04	0.51	0.06	0.31

5 Conclusion

The ASA ethical statement (ASA 2000) encourages statisticians to rely on transparent procedures. If transparency is not incentive-compatible under one institutional regime, perhaps one can find another regime in which it is. In the case of the econometric expert witness, such a regime is not out of the question. This paper has proposed a rule that would induce transparency in econometric consulting. Transparency is a minimal requirement for ethical procedures in such econometric consulting, and it represents a significant step towards the establishment of a code of ethics for the counterpart of statistical consulting in economics. The larger role of statistical ethics is to remind the statistician that, even when he is a member of a research group or an expert witness, he is part of the larger statistical community.[19] One way to think about severe sanctions or trial by resampling, which we propose above, is to make such thoughts incentive-compatible.

[19]This is perhaps not unrelated to the question of why Bayesians randomize posed by di Finetti, Diaconis (1998). ASA 2000 is explicit about responsibilities to the wider community; see pp. 2-4, 10.

Bibliography

Ashenfelter, Orley and David E. Bloom 1984. “Models of Arbitrator Behavior: Theory and Evidence.” *American Economic Review* **74**: 111-24.

Ashenfelter, Orley, Janet Currie, Henry S. Farber and Matthew Spiegel 1992. “An Experimental Comparison of Dispute Rates in Alternative Arbitration Systems.” *Econometrica* **60**: 1407-1433.

American Statistical Association. 2000. *Ethical Guidelines for Statistical Practice*. Alexandria VA.

Andrews, D.F, P. J. Bickel, F. R. Hampel, P. J. Huber, W. H. Rogers and J. W. Tukey. 1972. *Robust Estimates of Location*. Princeton: Princeton University Press.

Akerlof, George A. 1970. “The Market for ‘Lemons’.” *Quarterly Journal of Economics* **84**: 488-500.

Camerer, Colin F., and Richard H. Thaler 1995. “Anomalies: Ultimatums, Dictators and Manners,” *Journal of Economic Perspectives*, 9:2 (Spring), 209-219.

Crawford, Vincent P. 1979. “On Complusory-Arbitration Schemes.” *Journal of Political Economy* **87**: 131-59.

Deming W. Edwards. 1965. “Principles of Professional Statistical Practice.” *The Annals of Mathematical Statistics* **36**: 1883-1900.

Denton, Frank. 1985. “Data Mining as an Industry.” *Review of Economics and Statistics* **57**: 124-127.

De Finetti, Bruno. 1972. *Probability, Induction and Statistics*. New York: John Wiley.

Diaconis, Persi. 1998. “Mysticism in Statistics: From the Bible Codes to the Cult of Fisher.” Institute of Mathematical Statistics Presidential Lecture. Dallas.

Feigenbaum, Susan and David M. Levy. 1996. “The Technological Obsolescence of Scientific Fraud.” *Rationality and Society* **8**: 261-276.

Freedman, D. 1984. “On Bootstrapping Two-Stage Least-Squares Estimates in Stationary Linear Models.” *Annals of Statistics* **12**: 827-842.

Froeb, Luke M. and Bruce H. Kobayashi. 1996. “Naive, Biased, yet Bayesian: Can Juries Interpret Selectively Produced Evidence?” *The Journal of Law, Economics and Organization* **12**: 257-276.

Gardiner, John. 1996. “What and Where are Statistical Ethics.” Presented at the Joint Statistical Meetings. Chicago. Available at http://www.tcnj.edu/~asaethic/asaweb2.html

Gorlin, Rena A. 1999. Editor. *Codes of Professional Responsibility*. Washington: Bureau of National Affairs.

Hoffman, Elizabeth, Kevin McCabe, and Vernon L. Smith 1999. "Social Distance and Other-Regarding Behavior in Dictator Games: Reply," *American Economic Review*, 89:1 (March), 340-341.

Hoffman, Elizabeth, Kevin A. McCabe, and Vernon L. Smith 1996. "Social Distance and Other-Regarding Behavior in Dictator Games." *American Economic Review* 86:3 (June), 653-660

Houser, Daniel. 2005. "Experimental Ethics." Public Choice Working Paper.

International Statistical Institute. 1985 *Declaration on Professional Ethics*. 1985. Available at http://www.cbs.nl/isi/ethics.htm

Leamer, Edward E. 1983. "Let's Take the Con Out of Econometrics." *American Economic Review* **73**: 31-43.

Levy, David M. 1999/2000. "Non-normality and Exploratory Data Analysis: Problem and solution." *Econometric Theory* **15**: 427-28; **16**: 296-97.

Levy, David M. and Sandra J. Peart. 2005. "The Simple Analytics of Sympathetic Exchange." Public Choice Working Paper.

Phillips, Peter C. B. 1983. "Exact Small Sample Theory in the Simultaneous Equations Models." *Handbook of Econometrics*. Edited by Zvi Griliches and Michael D. Intriligator. Amsterdam.

Posner, Richard A. 1999. "An Economic Approach to Legal Evidence." *Stanford Law Review* **51:** 1477-1546.

Sally, David. 2001. "On Sympathy and Games." *Journal of Economic Behavior & Organization* 44: 1-30.

Savage, Leonard J. 1972. *Foundations of Statistics*. Second revised edition. New York.

Tullock, Gordon. 1980. *Trials on Trial: The Pure Theory of Legal Procedure*. New York: Columbia University Press.

Vardeman, Stephen B. and Max D. Morris. 2003. "Statistics and Ethics: Some Advice for Young Statisticians." American Statistician **57**: 21-26.

White, Kenneth J. 1997. *Shazam: Econometrics Computer Program (8.0)* New York: McGraw-Hill.