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REVIEWS

Joseph B. Kadane (Ed.), *Robustness of Bayesian Analyses.* Amsterdam and New York, North Holland, 1984. xii + 310 pp. $57.75

This book is the fourth one in the series "Studies in Bayesian Econometrics." It is well-known that there are many similarities between econometrics and psychometrics, and that differences between these two forms of applied statistics are mainly a question of emphasis. Econometricians have emphasized asymmetric dependency models for time series data, and psychometricians have emphasized symmetric interdependency models for cross-sectional data. Given the basic similarity between the two fields it is consequently of interest to readers of *Psychometrika* to find out if similar studies in Bayesian psychometrics would be of use.

In this respect the book is disappointing. Most of the papers are of a general statistical or even of a foundational nature, and have nothing to do with econometrics. The paper that is perhaps most content-oriented is, curiously enough, the classical paper by Edwards, Lindman, and Savage, reprinted from the *Psychological Review* of 1963. It is specifically addressed to psychologists, indeed it compares "such procedures as a Bayesian would employ in an article submitted to the *Journal of Experimental Psychology*, say, and those now typically found in that journal" (p. 3). There is little doubt that this is indeed a very useful paper, which eloquently presents and defends a moderate and quite reasonable Bayesian data analysis approach. But a brief glance at the applied journals, for instance the JEP, show that the classical methods have typically not been replaced by their Bayesian counterparts. Elementary statistics textbooks also show that regression and correlation, analysis of variance, the *t*-test, and classical contingency table analysis are still very much in command. The reasons seems to be, quite simply, that the classical procedures are quite satisfactory as data analysis techniques. They are easy to understand and explain, and they are based on descriptive statistics with clear intuitive and geometric meaning. It may very well be true that classical procedures are suboptimal, or even incoherent, from the inferential point of view, but all-in-all the scientific community does not seem to care a great deal for what statisticians and inductivists call inference. If we compare the current situation with that of twenty years ago what we do see is a shift from univariate to multivariate techniques, and from parametric to nonparametric techniques. Both are obvious consequences of the computer revolution. There is more space devoted to (computer-assisted or graphical) exploratory data analysis, and there is a tendency away from narrowly defined parametric statistical models that are the bread-and-butter of both classical and Bayesian statistical analysis.

Robust statistics is one such trend away from precisely specified parametric models in the direction of much more general supermodels or even nonparametric models. Ordinarily robustness is defined in terms of outlying observations or distributions with heavy tails. In Bayesian robustness studies, which are discussed and constructed in the book under review, the emphasis is on the robustness against choice of prior distribution. It is a common, although somewhat superficial, criticism of Bayesian statistics that the results of the analysis depend on the prior distribution, which is essentially subjective. This is considered to be contrary to common scientific practice. In the Edwards et al. paper the principle of *stable estimation* is proposed, which lists some properties a Bayesian procedure must have in order to be robust against misspecification of the prior. Because the paper is mainly intended for psychologists it unfortunately pays a great deal of attention to the testing of sharp null hypotheses. In the second paper, by Berger, a much more far-reaching overview of the robust Bayesian approach is given, covering a tremendous amount of material. Berger's approach allows for approximate specification of the prior, and for the option of letting the choice of the prior depend on the data. The paper has more than 250 references, and goes into many, perhaps too many, foundational aspects. There are useful comments by Brown, Hill, Kadane, and Lindley appended to the paper. If one likes foundational discussions, and if one is more or less convinced that the Bayesian approach to statistics is a reasonable one, then this paper is very useful indeed. On the other hand it treats so many different topics that it is necessarily quite superficial. The third paper in the volume is by Kadane and Chuang, reprinted from the *Annals of Statistics*, 1978. It treats robustness in a very general decision theory framework. If loss functions converge, and probability distributions converge, we can investigate whether optimal decisions converge too. If this is the case, the decision problem is said to be *stable*. These notions of stability, which are linked with various modes of convergence, are studied in detail. The fourth paper is a reprint of Chuangs dissertation, which goes even deeper into the same stability questions. The material in these two parts of the book is very technical, and neither specifically Bayesian nor even vaguely related to econometrics. The final paper in the book is quite another matter. It is written by Polasek, and it deals with hierarchical regression models. These models can be presented from a Bayesian point of view, but they can equally well be presented as random coefficient models in a frequentist framework. Polasek gives a very interesting matrix-algebraic discussion of these hierarchical models and applies them to a number of concrete econometric examples. The paper is very different from the rest of the book, which is definitely oriented towards foundations.

This reviewer has the problem that he happens to like foundational discussions, but does not think them to be of much importance for practical data analysis. It is not at all clear if and in what sense, statistics really needs foundations. All attempts to justify induction, or inference, are bound to fail. Logical justification of induction is impossible, and psychological justification is unnecessary. To construct a certain decision theoretic calculus, and to say that anybody who does not use this calculus is incoherent, is just a trick, which smacks of intolerance. The recent developments in statistics seem to indicate that the problem with classical statistics is not the fact that it does not incorporate prior information by using an explicit prior distribution, but the fact that it imposes far too much prior information by using very strong and unrealistic models. These strong models were needed in precomputer days to take over part of the computational burden, but they are much less needed now. In other words: the problems are in the likelihood, not in the prior. They are in the theory that classical and Bayesian statistics have in common, not in the part that divides them.

As a consequence many of the refinements introduced by robust Bayesianism are quite marginal, as are many of the refinements introduced by the classical robustness school. The model is still taken very seriously, or is replaced by a supermodel which is taken very seriously. As we have argued, the model is really the place where the prior information enters the data analysis, and the choice of the model is often as arbitrary as the choice of the prior. And, as Berger acknowledges in this book, far more influential. Thus the book can perhaps be recommended to philosophically oriented statisticians, but hardly to econometricians, and certainly not to psychometricians. The long paper by Polasek on hierarchical regression models is elegant and useful, but this is hardly enough.

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