*ISSN 1973-2201* *STATISTICA, anno LXXXIV, n. 2, 2024*
*DOI:* https://doi.org/10.60923/issn.1973-2201/20666

# DISCUSSION OF THE PAPER "CONNECTING MODEL-BASED AND MODEL-FREE APPROACHES TO LINEAR LEAST SQUARES REGRESSION" BY LUTZ DÜMBGEN AND LAURIE DAVIES (2024)

Clintin P. Davis-Stober [1]
*Department of Psychological Sciences, MU Institute of Data Science and Informatics, University of Missouri, Columbia, Missouri, United States*
Richard D. Morey
*School of Psychology, Cardiff University, Cardiff, United Kingdom*

Dümbgen and Davies (2024) provide a model-free perspective on the linear model along with an alternative interpretation of traditional $p$-values in that context. This is a valuable perspective and we agree with Davies' critique of the "truth-based" approach to statistics: parameters do not exist, and hence any approach claiming to infer something about true parameters is immediately suspect (Davies, 2024). This view of statistical models has a long history, with Fisher and Box expressing related views. How, then, do we square the need for inference in research with the impossibility of statistical inference? We argue that truth-based methods have a usefulness as thought experiments, - they can be part of an evidence base for an eventual inference, but cannot be used directly for inferential purposes.

In this sense, a statistical inference can be used as a one-way "skepticism pump." For instance, a large $p$ value warns you that similarly evidential results might be obtained when the parameter of interest is either positive or negative, and hence the data should not be used for the corresponding practical inference, i.e., our skepticism about the practical inference increases. We regard the opposite situation—a small $p$ value leading to a strong inference about the sign of a parameter—as problematic, because obviously the parameter does not exist. A researcher must bring more information to bear, and cannot pass off responsibility for the inference to the statistical procedure.

From this perspective, we can connect the approach of Dümbgen and Davies (2024), and many of the points raised by Davies (2024), to the "random conclusions" approach of Davis-Stober *et al.* (2024), which attempts to evaluate the accuracy of an estimator, say sample means, by comparing it to an estimation process that, by design, randomizes

[1] Corresponding Author. E-mail: stoberc@missouri.edu

important features of the data. Couched in a narrative of two labs performing identical treatment/control experiments, Davis-Stober *et al.* (2024) compares the sampling distribution of a pair of sample means to an estimation process in which the probability of the treatment group mean being larger than the control group mean is $\frac{1}{2}$, irrespective of the data. This process yields *random conclusions* about which sample mean is larger than the other.

The argument is simple: it is problematic if the sampling distribution of a random conclusions estimator well-approximates that of sample means, under a given combination of sample size and effect size. The aim of this approach is not to 'discover' a true underlying model, but to evaluate standard modeling processes against an easily understood benchmark with universally agreed-upon negative properties. In short, it is a one-way skepticism pump, meant to increase our skepticism about our ability to draw inferences from data in particular situations. While the random conclusions approach defines estimation accuracy via mean squared error, it is used primarily as a comparison index. As described in Davis-Stober *et al.* (2024), the random conclusions estimator can be compared to standard estimators via Kullback-Liebler divergence, or similar, methods. The existence of true parameters is not central to this approach, as the crux of the argument is that standard approaches should be distinguishable, in some formal sense, from processes which generate random conclusions about data - see also (Davis-Stober *et al.*, 2018). This type of comparison dovetails nicely, at least conceptually, with the approach of Dümbgen and Davies (2024), which eschews notions of the existence of true parameters in favor of approximating fixed real data with randomly generated data from the model-free process. Future work could apply the approximation methods developed in the target articles to such benchmark processes.

## References

L. Davies (2024). *Truth, ontology, honesty, approximation, indoctrination and statistics with special reference to high dimensional linear regression*. Working Paper.

C. P. Davis-Stober, J. Dana, D. Kellen, S. D. McMullin, W. Bonifay (2024). *Better accuracy for better science... through random conclusions*. Perspectives on Psychological Science, 19, no. 1, pp. 223–243.

C. P. Davis-Stober, J. Dana, J. N. Rouder (2018). *Estimation accuracy in the psychological sciences*. PloS one, 13, no. 11, p. e0207239.

L. Dümbgen, L. Davies (2024). *Connecting model-based and model-free approaches to linear least squares regression*. Statistica, 84, no. 2, pp. 65–81.