

Berk, R. (2004). *Regression Analysis: A Constructive Critique*. Thousand Oaks, CA: Sage. 259 pp.

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Just about all the statistics books I've seen—including my own—are very much in the form of advertisements for statistics. We fill our books with success stories of challenges that were resolved by some method we are recommending. Even when we list some open problems at the end, we have the confident feeling that they will soon be resolved with some additional elaborations of our preferred approach.

Richard Berk's interesting new book on regression analysis is different. It has no success stories at all; rather, the book is an introduction to linear regression, mixed with warnings about how regression analysis can mislead. Berk's general recommendation is to treat regression as a form of data description (a generalization of taking the difference between two samples). He emphasizes that statistical inference (standard errors, hypothesis tests, and confidence intervals) require assumptions that are commonly not tested, and often not testable, and that causal inference requires yet another layer of assumptions about sampling and selection. As he puts it, "If the goal is to do more than describe the data on hand, information must be introduced that cannot be contained in the data themselves" (p. 19).

In addition to expressing valuable skepticism, Berk makes some important practical points. He focuses on the mean—the deterministic part of the regression model—rather than the errors. Most statistics texts seem to make the mistake of talking on and on about the distribution of the errors and the variance function, but it is the deterministic part that is generally most important. I also like that in Section 3.6, Berk presents transformations as a way to get linearity (not normality or equal variance, which are typically much less important). I agree with Berk's skepticism in chapter 9 about traditional "regression diagnostics." In my experience, outliers and nonnormality are not the key concerns, and what is more important is to get a sense of what the model is doing and how it is being fit to the data.

In some places, Berk is less skeptical than I would be. For example, on page 68, he writes, "The null hypothesis is either true or false." Actually, I would go further: In any problem I've ever worked on, the null hypothesis is false. Mathematically, the null hypothesis in regression is that some beta equals 0, and in social and environmental science, the true beta (as would be seen by gathering data from a very large population) is never exactly 0. I do think that hypothesis testing can be useful—for example, it can tell you that you can be very sure that beta is greater than 0 or that beta is less than 0 and whether the data are sufficient to estimate beta precisely—but we know ahead of time that beta does not equal 0. To my mind, this implies that much of classical testing is irrelevant to applications, which fits with Berk's focus on data description rather than formal statistical inference.

My main area of disappointment with this book is that its worked examples all use fake data—Berk discusses a lot of interesting examples but then does not follow up with the details. For example, Section 2.1.1 brings up the Donohue and Levitt (2001) example of abortion and crime, and I was looking forward to Berk's more detailed analysis of the problem; however, he never returns to the example later in the book. I would have learned more about Berk's perspective on regression and causal inference if he had applied it in detail to some

real-data examples. I would also have liked to have seen some success stories, but we can go to many other books for these. I also think the discussion of models would be strengthened by some discussion of interactions. Perhaps a second edition will flesh out some of the critiques in the context of the applied examples that Berk is clearly familiar with, and maybe even add a success story or two.

In the meantime, this book lives up to its subtitle as a “constructive critique” that complements the more standard “how-to” treatments of regression, and I hope that many students and practitioners will be inspired by it to think harder about the connections between their data analysis, their statistical models, and their social science research goals.

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