Chapter 12
Conclusion

We have covered a lot of ground in this book. We began in Chap. 2 by discussing the process of scientific research, including the philosophical underpinnings of the scientific method. As we discussed, this process begins with the construction of a succinct research question and hypothesis that has the key property of being falsifiable. As we showed, the goal of scientific research is to falsify hypotheses derived from larger explantions for how the world works. We can never prove our hypotheses to be true, and so the best we can do is rule out bad hypotheses. Explanations that generate hypotheses that cannot be rejected after extended testing eventually become recognized as theories, the ultimate status for a scientific explanation of the world.

The process of hypothesis testing requires the collection of data from the real world, often via observation, interviews, and surveys. We discussed the difficulties and goals of data collection in Chap. 3, but we barely scratched the surface. Entire courses are offered on research methodology, including courses only on sampling methods. The books for such courses range from general books on the theory and practice of research (e.g., Babbie 2004; Firebaugh 2008; Lieberson 1987) to books on the technical details of data collection (e.g., Dillman et al. 2009).

In Chap. 4, we began discussing how to summarize data with basic descriptive measures that reflect the center and spread of the distribution of variables. We then discussed the limitations of such measures and their misuse. There are a number of excellent and entertaining books that discuss an array of ways in which statistics can be abused (e.g., Campbell 2004; Hooke 1983; Huff 1993). Such books are not only often fun to read, but they are also very instructive in showing how to be a critical consumer of statistical data and arguments based on them.

We turned our attention in Chap. 5 away from descriptive methods and discussed probability theory. Probability is the foundation on which inferential statistics is based, and understanding probability is crucial to understanding and evaluating statistical arguments. Our discussion of probability, while fairly extensive, was not completely thorough. Other excellent books exist that cover probability theory in much greater depth (e.g., DeGroot and Schervish 2012). While most people think in probabilistic terms—and probabilistic terminology permeates our language

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and discussions—people are often bad at formal probabilistic reasoning. We often overestimate or underestimate probabilities and evaluate them incorrectly, reaching poor conclusions. Although we discussed some of the ways in which probabilistic reasoning can be flawed, there are a number of books available that provide entertaining discussions of common fallacies in probabilistic thinking and mathematical thinking more generally (e.g., Bunch 1997; Campbell 2004; Mlodinow 2008; Paulos 2001). There are also several books that show how such fallacious reasoning and analyses have led to real-world policy emphases that do not serve the public interest (e.g., Agin 2006; Pigliucci 2010).

Chapter 6 illustrated one of the most crucial theorems—the Central Limit Theorem—that helps us make the leap from deductive, probabilistic thinking to more inductive, inferential reasoning. That chapter shows the basis for understanding why small, random samples are all that is needed to make valid and precise statements about huge, even infinite, populations. We also discussed how we can use inferential methods to evaluate statistical hypotheses. The most important idea, one that has been repeated again and again in subsequent chapters, is that classical statistical hypothesis testing involves evaluating the probability of observing the sample data we obtained if the hypothesis we are evaluating were true. If that probability is small, we then reject the hypothesis (see DeGroot and Schervish 2012). This approach to statistical hypothesis testing seems backwards to many and I believe is what makes learning statistics difficult. In all fairness, one should become familiar with the criticism of the approach to statistics involving p-values that we discussed in this book (see Ziliak and McCloskey 2008). Furthermore, there is a competing paradigm of statistics—Bayesian statistics—that more directly assesses the probability that hypotheses are true and corresponds better, arguably, to how people actually think. Numerous, more advanced statistical courses and books are available to learn more about this approach to statistics (see Lynch 2007).

Chapters 7 through 9 extended the basic precepts of statistical inference and hypothesis testing to different types of data, that is, data measured at different levels. While we have covered some basic methods for assessing relationships between different combinations of nominal, ordinal, and continuous variables, we have limited our discussion to some key, basic approaches. Entire courses can certainly be taken on methods for each combination of different types of measures. Such courses are usually taken after a basic course on multiple regression modeling, the basics of which we discussed in Chap. 10.

Chapter 10 began with a discussion of the notion of causality and the difficulties with establishing that a relationship between two variables is a causal one. As we discussed, experimental methods are usually viewed as the gold standard for establishing that relationships are causal, but in most social science research, experimental methods are impossible to employ. Multiple regression serves as a key method for establishing the relationship between two or more variables while simultaneously controlling out relationships that potentially explain the relationship of interest (see Morgan and Winship 2007, for extensive discussion of the state of causal modeling in social science). Regression modeling is a fundamental approach to handling "multivariate" data, that is, multiple variables, and we barely scratched the surface in introducing it. The next course one usually takes in statistics is a detailed course on multiple regression modeling that spells out the statistical assumptions that underlie the model, the consequences of violating those assumptions, and methods for compensating for them. There are a number of excellent books available that elaborate multiple regression methods and show how it can be extended in numerous ways to handle different data contexts, like time series data and panel data (e.g., Fox 2008; Gujarati and Porter 2009).

Finally, in Chap. 11, we discussed how to present the results of statistical analyses. Learning how to present results of statistical analyses via tables and figures is easily as important as learning how to conduct the analysis itself. Poor presentation can make the results unintelligible at best and misleading at worst. From a practical perspective, if you have gone to the trouble to conduct good analyses, you should certainly want to convey what you've found in a way that people can follow! Chap. 11 provided very basic rules for doing so, but as with the material in other chapters, there are many books on the topic that should be explored (e.g., Cleveland 1993).

In sum, we have covered a lot of ground in this book, but there is far far more out there to be learned. I hope that you have found the material we covered to be interesting, and even fun, and I wish you luck in conducting your own analyses!