devices that sometimes empower observational studies to yield credible answers, including disambiguation, multiple control groups, and coherence among several outcomes, and, crucially, by promulgating sensitivity analysis as a central activity for demonstrating when plausible unmeasured biases cannot overturn a causal inference. Moreover, knowledge of these creative devices, which is unlikely learned from the sphere of randomized studies, proves valuable for the design of both randomized and observational studies, and the book inspires greater use of sensitivity analysis in randomized studies, which is sorely needed. *Design of Observational Studies* has sparked lines of enquiry for improving my own specialty area of statistical science, randomized vaccine efficacy trials.

A limitation—or simply a fact—of the book is that it almost exclusively considers the technique of matching for minimizing observable biases, so much so that the book may have been appropriately titled, "*Design of Matched Observational Studies*." While the principles and concepts translate well to unmatched techniques such as regression, the absence of discussion about how the translation is made may make it hard for some readers to apply the book's ideas to the design of unmatched studies. I found myself wishing for an extra section that tutors the reader on how to draw these lines. But this is slight criticism compared to my high praise for the book as a treasure of statistical history, philosophy, and principles for sound and creative study design that would benefit almost any statistician.

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FITZMAURICE, G., DAVIDIAN, M., VERBEKE, G., and MOLENBERGHS, G. (eds). **Longitudinal Data Analysis.** Chapman & Hall/CRC, New York, 2008. viii + 632 pp. \$94.95/£59.99. ISBN 9781584886587.

Longitudinal Data Analysis is Chapman & Hall's first entry in its new series *Handbooks of Modern Statistical Methods.* The choice of topic is natural: longitudinal data analysis has a rich history in a number of fields, and new avenues of investigation continue to be opened up. The volume's editors have assembled a world-class panel of contributors; many have made seminal contributions to the field (this includes the editors themselves).

Immediately apparent is the uniformity of notation and writing style not typically found in volumes of this kind. The editors clearly have taken great care to ensure a whole document rather than a disjointed patchwork typical of similar collections. Chapters reflect contributor diversity while suppressing distracting idiosyncrasies. Chapman & Hall would do well to emulate this feature in future entries to the series.

The book is divided into five parts: historical overview, parametric modeling, non- and semi-parametric methods, joint models, and incomplete data. Each chapter is self-contained, which works well for readers who choose to read individual chapters, but it also leads to noticeable overlap in content: for example, generalized linear models and the random effects model are exhaustively described in early chapters, but then reintroduced—in detail—in each of several subsequent chapters.

The emphasis of the volume is overwhelmingly on regression models. This is especially true of the early chapters, which cover material that is by now 25–30 years removed from first appearance in the statistical literature. But a comprehensive account of longitudinal data analysis has to start somewhere, and Part II provides a full accounting of generalized linear models, random effects models, nonlinear regression, and generalized estimating equations. Augmenting the standard descriptions are broad historical perspective, some new insights, and several interesting examples.

Part III on non- and semi-parametric modeling is a modern and forward-looking summary of smoothing and functional data analysis, a truly unique contribution that would make an outstanding monograph on its own. Part IV comprises several chapters on joint modeling, a vague term typically used to label models for joint distribution of repeated measures and event-history data. The editors have a broader meaning in mind: Part IV contains a concise but exemplary chapter on repeated measures and event times (Chapter 15, by Diggle, Henderson, and Philipson), but also includes chapters on multivariate repeated measures processes and latent variable models for high-dimensional data (where more extensions of multilevel regression are encountered). The diversity of interesting examples, rather than a coherent description of "joint modeling," is the strength of this chapter.

A brief digression: In reading Parts III and IV, one is struck by the remarkably wide-ranging utility of the hierarchical generalized linear model (a.k.a. generalized linear mixed model, random effects model) as a tool for inference from longitudinal data. Multilevel regression formulations figure prominently in growth curve modeling, regression splines, functional data analysis, dimension reduction, and multivariate longitudinal outcomes. Parts III and IV are a testament to the durability and scope of the generalized linear model in handling both low- and high-dimensional data. A number of new methods having exotic nomenclature still reduce to a (hierarchical) generalized linear model of one kind or another.

With chapters on missing observations, dropout, and causal inference, Part V takes a sweeping view of the term "missing data." While it is true that a causal inference via the potential outcomes model is a missing data problem, drawing causal inferences has become so central to the collection and analysis of longitudinal data that it deserves its own heading (it surely deserves its own entry in the Handbook series). The missing data chapters are well-written and comprehensive: Rod Little (Chapter 18) has contributed a short encyclopedia of models and methods, and Kenward and Carpenter (Chapter 21) have given a nice summary of imputation methods.

Several individual chapters deserve special mention: Chapter 1 on history (Fitzmaurice and Molenberghs) is perhaps the most comprehensive published account of the development of longitudinal data methods, giving a detailed lineage of modern approaches; in Chapter 5 on nonlinear models, Marie Davidian has composed a clear, beautifully written survey, illustrated by succinct but diverse and interesting examples. Expansion of the interface between statistics and biology makes this required reading for every graduate student and new investigator in biostatistics. Andrea Rotnitzky's contribution on inverse probability weighting (Chapter 20) stands apart for its crisp and transparent writing on a topic many still find difficult. It provides new historical perspectives and gives lucid descriptions of double robustness without sacrificing technical content. Chapter 23 on causal effects of time-varying exposures (Robins and Hernan), though long and in some places overly dense, gives an outstanding review of key issues and, perhaps more importantly, a compare-and-contrast for several different modeling approaches.

The editors made solid choices for both topics and contributors, but I was struck by the absence of material on three specific topics: study design, modeling of covariance structure, and Bayesian methods for model specification and inference. Design is a topic that receives surprisingly scant treatment in textbooks on longitudinal data, despite its obvious importance to researchers in just about every field of research (Diggle et al., 2002, is an exception). Most of the chapters view covariance modeling as a route to efficient estimation of means, or as a byproduct of certain model formulations, but associations can be of direct interest in their own right—consider biomarker analyses for example. Finally, given the preponderance of hierarchical models in the book, the scant attention given to Bayesian inference was surprising. Depending on their perspective, some readers may notice other omissions; hidden Markov models, difference-of-difference methods, and predictive inference from biomarkers come to mind. There is surprisingly little material on longitudinal versus cross-sectional effects, which could merit its own chapter. But longitudinal data analysis is a vast topic—perhaps too vast to address in a single volume. Choices have to be made, and the editors are entitled to reflect their view of the field. More generally, the first chapter on historical developments would have been nicely balanced by ending with a chapter on emerging topics and new directions. Longitudinal data analysis is alive and expanding, which leaves hope that these topics will appear in a future edition.

Experienced researchers and those new to the field will find useful material here. Seasoned investigators will be familiar with most of the book's content, but several chapters provide fresh insights. For graduate students and new researchers, the book provides a useful introduction and comprehensive reference material for the topics it covers. Case studies and software enable readers to implement some methods described in the book, with supplemental datasets and programs appearing on a useful website.

The material does overlap to some degree with existing monographs on longitudinal data and missing data. But in several places the book moves well beyond those, notably with respect to non- and semi-parametric models and causal inference.

This ambitious project largely succeeds in summarizing broad categories of methods for analysis, delving into a satisfying number of subtleties, providing new insights on commonly used models and methods, and illustrating capably with interesting examples. The writing is uniformly strong, even extraordinary in some chapters. A strong inaugural volume for Chapman & Hall's new series on modern statistical methods, *Longitudinal Data Analysis* provides an outstanding model for future entries.

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DMITRIENKO, A., TAMHANE, A. C., and BRETZ, F. (eds). **Multiple Testing Problems in Pharmaceutical Statistics.** CRC Press, New York, 2009. xvi + 304 pp. $89.95/£57.99. ISBN 9781584889847.

This book presents results from problems of testing multiple hypotheses in the context of drug development. The editors state the intended audience consists of biostatisticians engaged in clinical research, adding that the chapters contain enough introductory material to make them accessible to pharmaceutical researchers. The first chapter presents an overview of the ideas of the book in a context of regulation of drug development. The reader can see a division of the rest of the book in two pieces: The first, consisting of Chapters 1 through 5, written mostly by the editors themselves, and the last two chapters, with a different set of authors, which do not seem to flow together as well as the first part. The sixth chapter reaches too broadly to describe adaptive designs and sequential analysis. The final chapter, which covers problems from microarray data, is more focused than Chapter 6, and is accessible to readers with knowledge of experimental design and cluster analysis. Each chapter ends with code for either `SAS` or `R` to run some of the analyses mentioned. Through most of the book, the perspective of regulators appears as a consideration in design.

The first part of the book is a cohesive exploration of the uses of methods of multiple hypothesis testing. These