describes some of the aspects of analysis for designs where multiple responses are collected. Because most experiments have this feature, understanding the opportunities and challenges for this situation is essential reading for practitioners. Chapter 13 is a collection of short sections on a number of other specialized designs, including screening, equileverage, optimal, space-filling, trend-free, and mixture designs.

Chapter 14, "Tying It All Together," briefly discusses the difficult task of choosing between different designs when planning an experiment. This chapter reinforces my belief that learning this aspect of design of experiments is most challenging, both because of how we teach design (cleanly compartmentalized into tidy chunks with questions posed to fit precisely into a category) and because of the ever-increasing breadth of tools available. The exercises at the conclusion of this chapter help the reader gain experience with design selection and pose many thought-provoking questions that will challenge even the most seasoned statistician.

Already an extensive volume on the subject, this book contains a wealth of information. However, on my wish list for additional topics would be more discussion about the different roles of experimentation, from exploration, to screening for important factors, to response surface methods for characterizing and optimizing the relationship between the key factors and the response, to confirmatory experiments near the chosen optimum. Matching types of designs to their intended purposes is another area that is difficult for those studying design of experiment, and direct discussion can greatly help accelerate this understanding. In addition, it would be beneficial to present some of the criteria and graphical tools that are available to compare different potential designs. This could help formalize the numerous trade-offs between the many aspects of a good design.

Overall, *Modern Experimental Design* is a must-have reference for anyone who will be designing experiments or for statisticians interested in remaining on the leading edge of this important area. I thoroughly enjoyed reading this well-written and comprehensive book, both for the careful and clear synthesis of the new research in this area and for the many insightful comments that help connect the details of the methods to the big picture.

Christine M. ANDERSON-COOK
Los Alamos National Laboratory

Measurement Error in Nonlinear Models: A Modern Perspective (2nd ed.).

Raymond J. CARROLL, David RUPPERT, Leonard A. STEFANSKI, and Ciprian M. CRAINICEANU. Boca Raton, FL: Chapman & Hall/CRC, 2006. ISBN 1-58488-633-1. xxviii + 455 pp. $89.95.

New editions of statistics texts vary considerably in their ambitiousness, from superficial face-lifts to complete rewrites. The current book can be placed toward the extreme of the latter end of this spectrum. Compared with the 1995 first edition, the book has expanded from 305 to 455 pages; the chapters have been reorganized, resulting in a net increase of one chapter and an appendix; and even the author list has grown by one (Crainiceanu). Clearly, the authors have taken a very comprehensive approach, rewriting the entire text. This seems to have been done both to accommodate an explosion of new research in the field of measurement error and also in the interest of improving the pedagogy and scholarship.

The former introductory chapter has now been divided into two chapters, one that introduces the measurement error problem in general, presents a large number of examples where this problem arises, and gives a bit of overview and another that introduces basic concepts important to the study of measurement error. A chapter has been added on longitudinal data and mixed models, and chapters on semiparametric regression and Bayesian methods have been so thoroughly rewritten and updated as to be essentially new. I found the Bayesian chapter to be particularly well written and edifying. Other chapters receiving major updates are those on score function methods, nonparametric (density and regression) estimation, and survival data. The authors also include chapters on linear regression and attenuation (essentially the background material from the linear model case), regression calibration, simulation extrapolation (SIMEX), instrumental variables, likelihood and quasi-likelihood, hypothesis testing, and response variable error. All of these chapters, as well as a very useful appendix containing estimating function theory and other important background material, have been rewritten. In some cases, examples have been added or reworked to improve the exposition, and many small simulation studies have been included to illustrate problems with naive methods and various theoretical results. Technical details specific to each chapter have been moved to a second appendix.

Although the statistical and mathematical sophistication required of the reader is not extreme, the material here is far from easy; those without substantial familiarity with the statistics of measurement error will not benefit greatly from this book without careful study. The authors, who include the foremost experts in the field, have done an outstanding job pulling together a large and rapidly growing literature and presenting it in a coherent form. Their writing style is often refreshingly informal, but in places a bit vague. Nevertheless, they are to be congratulated for producing a first-rate book that will be an indispensable resource for researchers and other serious students of the statistics of measurement error.

Daniel B. HALL
University of Georgia

Linear Mixed Models: A Practical Guide Using Statistical Software.

Brady T. WEST, Kathleen B. WELCH, and Andrzej T. GAŁECKI. Boca Raton, FL: Chapman & Hall/CRC, 2007. ISBN 1-58488-480-0. xix + 353 pp. $79.95.

This text is a most welcome addition to the literature on regression models. West, Welch, and Gałecki have done a superb job addressing linear mixed model (LMM) applications using commonly available, state-of-the-art statistical software (notably SAS, SPSS, Stata, R/S–Plus, and HLM). The text is directed toward applied statisticians and researchers in search of a broad, accessible reference of linear models.

The authors begin with an introduction to LMMs and briefly discuss theoretical and software developments. The first chapter includes a discussion of data types (clustered vs. repeated vs. longitudinal), effect types (fixed vs. random), and other pertinent considerations (e.g., covariance structures, estimation techniques). Other topics covered are model selection strategies and post hoc diagnostics. The remaining five chapters cover specific types of LMMs, including two- and three-level models for clustered data, models for repeated measures, random coefficient models for longitudinal data, and models for clustered longitudinal data. The text concludes with three useful appendixes. The first appendix provides supplementary material, much of which is available on companion websites. It also includes an introductory discussion of matrix algebra operations and a survey of linear mixed model procedures. The second appendix details calculations of the marginal variance–covariance matrix, and the third lists acronyms used in the book. The book ends with a list of cited references.

The book is organized thoughtfully and features a detailed table of contents, particularly useful for quick reference. Typeface is uniform, with important terms emphasized in bold. Tables are organized logically and figures presented clearly. Assuming negligible familiarity with the topic on the part of the reader, the second chapter presents a solid foundation to LMMs, introducing new vocabulary and explaining new concepts thoroughly. This presentation style will be appreciated by newcomers to the field. The many tables help summarize, compare, and contrast the differences between designs and software, easing comprehension of the difficult material. End-of-chapter summaries emphasize and reinforce important points. It is clear that the authors devoted tremendous effort to organizing and writing the text; their clear exposition makes it truly a joy to read.

Each chapter begins with a concise introduction to the model discussed in the chapter and an accompanying example chosen for illustration. In addition, each chapter contains a table with examples of the type of study design being discussed applied to different disciplines, such as sociology, education toxicology, medicine, biology, psychology, and business. This gives the reader an appreciation of the versatility of the presented methods. Most helpful are software-specific notes and the explanation of messages generated by the software. Suggested remedies to error messages are also provided. Code for each of the examples begins with reading in the data, something often—and unfortunately—taken for granted.

In summary, this book is all the authors intend it to be and more. It is one of those rare texts with no glaring omissions or obvious shortcomings. The book consolidates syntax germane to linear mixed models for most major software

packages, obviating the need to consult multiple platform-specific texts. Most importantly, the material is presented in an easy-to-read, sensibly organized fashion, making the text valuable as a pedagogic aid and a ready reference. In short, *Linear Mixed Models: A Practical Guide Using Statistical Software* is a must buy for the applied statistician and researcher alike.

<div style="text-align: right">

Gregory E. GILBERT
Medical University of South Carolina

</div>

Sampling Algorithms.

Yves TILLÉ. New York: Springer, 2006. ISBN 0-387-30814-8. xi + 216 pp. $74.95.

In modern survey statistics, sophisticated sample drawing techniques are used to improve the efficiency of estimates gained from the sample surveys. Recent developments in computer technology provide the necessary basis to apply these sampling mechanisms in complex real world applications. However, efficient sampling plans also are of great interest in modern statistics where massive numbers of samples have to be drawn efficiently. Yves Tillé's book provides a comprehensive overview of such sample drawing mechanisms, the so-called sampling algorithms, in a very clear and comprehensible way. The concise presentation of many sampling algorithms enables interested practitioners to easily apply or implement the methods in their own programs.

This book is based on the fundamental books of Brewer and Hanif (1983) and Hájek (1981), which give excellent overviews of unequal probability sampling. Although the theory of sampling algorithms is not new, recent improvements in computer technology suggest numerous and rapid advances in this area. Many of these latest developments are included in the book and serve to place the entire methodology into a convincing framework. Further, in contrast to most earlier publications, a strong focus was put on the implementability of the algorithms—an aspect that is very important for practitioners.

After an introduction, which contains some history and background of sampling algorithms as well as aims and an outline, the necessary notations and definitions are presented in chapter 2. A sample is simply an outcome of a vector of size N (finite population size), which indicates for each component $i = 1, \ldots, N$ the number of times unit i is drawn (these times thus sum to the sample size n). This vector covers samples with and without replacement. Several technical annotations sequentially build the framework for the illustrations of the sampling algorithms that come later. Finally, the chapter closes with a presentation of the point and variance estimators needed for this framework: the Hansen–Hurwitz and Horvitz–Thompson estimators.

When considering sample drawing mechanisms, one may apply highly different algorithmic techniques. These may differ, especially in implementability and in complexity with respect to n and N (which becomes evident in large-scale surveys). Advanced algorithms bypass the need to enumerate all possible samples and randomly draw one or more samples of this possibly very enumerative collection. Chapter 3 presents several kinds of algorithmic procedures, such as martingale, sequential, draw by draw, eliminatory, and rejective algorithms. Later methods are presented as special routines based on these general procedures.

Chapter 4 deals with sampling plans for simple random sampling. It may be viewed as an introductory chapter with less sophisticated designs and a first real application of the generalized algorithms from chapter 3 in a *user-friendly environment*.

Chapter 5 treats unequal probability designs. The chapter's general framework is based on exponential designs, from which most of the sampling in this chapter are derived. Based on a general expression, several sampling algorithms can be derived by changing the support, which is defined as a set of samples. The specialized designs considered throughout the chapter are Poisson sampling designs, the multinomial design, and conditional Poisson sampling.

Chapter 6 presents the splitting method. This method, which can be viewed as a general framework for unequal probability designs of fixed sample size without replacement, was developed in Deville and Tillé (1998). The splitting method also facilitates comparability of several unequal probability methods.

Chapter 7 covers unequal probability methods, which cannot be presented under either the exponential designs or the splitting method. The methods cover systematic and Sampford designs. In addition, related variance approximation and estimation methods are considered. This paragraph allows one to bypass calculation of second-order inclusion probabilities, which are needed for the

Sen–Yates–Grundy variance estimator, by applying approximations that consider only first-order inclusion probabilities.

Chapter 8 is dedicated to balanced sampling. In contrast to calibration estimation, where the calibration constraints are induced within the estimation process, balanced sampling uses the same constraints already within the sampling design. Thus, a balanced sampling design guarantees that the Horvitz–Thompson estimates of the balancing variables equal their totals (except for possible rounding errors). The solution of balanced sampling is achieved by the cube method proposed by Deville and Tillé (2004). The chapter concludes with variance approximations in balanced sampling. Chapter 9 gives an application of balanced sampling to a Swiss data set.

All readers will find the list of algorithms, abbreviations, and notation very useful. Also impressive are the numerous references: 166 references, 89 of which are from 1984 and later (hence after Brewer and Hanif 1983 and Hájek 1981), demonstrate the author's profound insight. The interested reader benefits from this rich source while having the opportunity to read deep details throughout the book. But the book also can be used by itself, especially if the focus is on implementing or using sampling algorithms.

The book provides many implementable algorithms that can be coded in any convenient language. Tillé and Matei also have published a package `sampling` for the statistical software R (*http://www.r-project.org* and *http://cran.r-project.org/src/contrib/Descriptions/sampling.html*). This package will surely serve as a helpful tool for generating samples from very different designs.

On my first read of the book, I found it very interesting from a scientific standpoint. As I was also investigating an application of balanced sampling in a sample survey for the German Federal Statistical Office, I became more appreciative of the practical aspects of this text.

I have one criticism, however. Even though the author gives some recommendations on conditional Poisson sampling and balanced sampling (Sec. 7.7), practitioners and computational statisticians will hardly find a comparative overview of the complexity and applicability of the different algorithms. It is noted that presenting such practical guidance would take many pages, and that this is not the main focus here. This void, of course, allows ambitious young researchers room to play.

To fully understand the book, the reader needs some knowledge of mathematical statistics on the level of Mittelhammer (1996) and Hogg, McKean, and Craig (2005) and survey statistics (e.g., Lohr 1999; Särndal, Swensson, and Wretman 1992). Some additional knowledge of computer programming or algorithms is not essential but would be helpful. Interested readers in computational statistics may also find this book useful for variance reduction techniques. Practitioners may find the text helpful while cross-reading it (perhaps skipping some of the sophisticated mathematical annotations). *Sampling Algorithms* will serve nicely as a textbook for graduate students in statistics or postgraduate students in applied sciences dealing with survey methodology. It will find the way to my lectures in the near future (as it already does in my research).

The author's aims are capably stated up front: "In view of the large number of publications, a synthesis is probably necessary. . . . The challenge of this book is to propose at the same time a unified theory of the sampling methods and tools that are directly applicable to practical situations," and, later, "Particular stress is given to a geometric representation of the sampling methods." He has done a wonderful job.

Personally, I feel that this book is a must for any survey researcher interested in sample selection procedures. It should be of great interest for practitioners who need to implement surveys, even if some investment is needed when reading it. The R routines will help facilitate the methods for those with little detailed knowledge of sampling algorithms and R; moreover, they also will support National Statistical Institutes to implement sophisticated sampling algorithms.

<div style="text-align: right">

Ralf MÜNNICH
University of Trier, Faculty IV

</div>

REFERENCES

Brewer, K. R. W., and Hanif, M. (1983), *Sampling With Unequal Probabilities*, New York: Springer.

Deville, J.-C., and Tillé, Y. (1998), "Unequal Probability Sampling Without Replacement Through a Splitting Method," *Biometrika*, 85, 215–227.

—— (2004), "Efficient Balanced Sampling: The Cube Method," *Biometrika*, 91, 893–912.

Hájek, J. (1981), *Sampling From a Finite Population*, New York: Marcel Dekker.