Measuring Business Cycles in Economic Time Series.

Regina Kaiser and Augustin Maravall. New York: Springer-Verlag, 2001. ISBN 0-387-95112-1. xv+ 190 pp. $59.95 (P).

This book studies the Hodrick–Prescott (HP) filter, one of the tools economists use to measure business cycles. Indeed, the book can be regarded as a user’s manual for the HP filter, discussing the filter’s characteristics, presenting a variety of equivalent derivations, pointing out several problems associated with its application, and contributing a number of extensions that address those problems.

The HP filter can be regarded as an approximate high-pass filter. When applied to quarterly data, it damps periodic components lasting 8 years or more and passes components at higher frequencies. One of its virtues is that it renders stationary a variety of trending processes, including both trend and difference stationary representations. Thus, knowledge about the exact nature of the trend is unnecessary for extracting a stationary measure of the cycle. Another of the HP filter’s virtues is that it provides a sensible measure of the business cycle for actual economies. For example, the HP measure for the U.S. corresponds closely to the business cycle chronology of the National Bureau of Economic Research. The filter is also optimal in the Wiener–Kolmogorov sense for a class of unobserved components models, although the properties of the class differ in several respects from conventional wisdom about business cycles.

Despite its many virtues, Kaiser and Maravall point out several problems associated with the HP filter. This discussion, along with proposals for solutions, forms the heart of the book. One especially important problem concerns the fact that the filter is two-sided. In practice, it is common to drop a dozen or so observations at the beginning and end of the sample and focus attention on points near the center. This is fine for historical analysis, but it is unsatisfactory for policy makers and others who must make decisions in real time.

Indeed, the endpoint problem has been a major obstacle to the filter’s adoption in policy circles. One of the book’s most important contributions is to show how to overcome this problem by incorporating forecasts and backcasts. Kaiser and Maravall demonstrate that this greatly reduces the variance and persistence of revisions in real-time measures of the cycle. This innovation is likely to make the HP filter much more popular among policy analysts, and I highly recommend the book to economists at policy institutions who track business cycles for a living.

As a user’s manual for the HP filter, the book is quite successful. Its title, however, suggests a broader perspective and is a bit misleading. The book really is not about measuring business cycles, and readers with broader interests are likely to be disappointed. For example, there is almost no discussion of business cycles in actual economies. Readers interested in empirical regularities about actual economies should consult the text of Stock and Watson (1999) and the references listed therein.

Similarly, although Kaiser and Maravall state that the business cycle literature has converged on this measure, the HP filter is in fact only one among many tools that economists use. Alternative measures are barely mentioned, and there is no discussion of their relative merits. If I were to use this book in a graduate class in economics, I would supplement it with readings on alternative methods. For example, Beveridge and Nelson (1981) define stochastic trends in terms of long horizon forecasts, Harvey (1989) discusses a broader class of unobserved components models, Baxter and King (1999) study other filters, and Kim and Nelson (1999) describe hidden Markov representations.

Not only is there less convergence than Kaiser and Maravall suggest, but the HP filter is actually somewhat controversial. One of the more serious criticisms concerns the potential for generating spurious cycles. Some economists think that trend reversion is an important feature of business cycles; that is, that expected growth is higher than average at the trough of recessions and lower than average at the peak of expansions. The Beveridge–Nelson definition captures this idea. Cochrane (1994) and Rotemberg and Woodford (1996) have estimated Beveridge–Nelson measures and find that trend reversion is indeed an important feature of U.S. business cycles. Yet HP measures can suggest the existence of business cycles even if there is no trend reversion in the data. For example, consider a random walk with drift. Expected growth is constant regardless of whether the series is at a local peak or a trough. Hence there is no trend reversion or business cycle component in the sense of Beveridge and Nelson. Yet there are cycles in an HP-filtered random walk. Its spectrum has a peak at roughly 8 years per cycle, and realizations oscillate in a way that resembles conventional notions of a business cycle. That there may be business cycles in HP-filtered data even if there are none in the Beveridge–Nelson sense has been interpreted as a problem for the HP measure. This seems especially relevant when evaluating business cycle models. By studying Beveridge–Nelson measures, Rotemberg and Woodford were able to diagnose important discrepancies between models and data that would not have been readily apparent in HP measures. Kaiser and Maravall discuss the “spurious cycle” criticism but do not come to grips with the full force of the argument.

It may be churlish to criticize Measuring Business Cycles in Economic Time Series for being more narrowly focused than advertised. My only excuse is that the title invites such a criticism by suggesting a broad perspective. A better title would have been “The Hodrick–Prescott Filter in Theory and Practice.” The book succeeds as a reference on the HP filter, and I recommend it to anyone seeking such a text.

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Continuous Stochastic Calculus With Applications to Finance.

Michael Meyer. Boca Raton, FL: Chapman and Hall, 2001. ISBN 1-58488-234-4. vi+ i+ 319 pp. $89.95.

The scope of the book is first to develop rigorously the theory of continuous-time martingales and stochastic integration, and then, in the final third, to give some applications of these methods to mathematical finance. By collecting this material in one textbook, the author claims to fill a gap in the existing literature. However, there actually are a couple of excellent texts on this subject [e.g., Elliott and Kopp (1999); Karatzas and Shreve (1998); Lamberton and Lapeyre (1996); Steele (2001), to name but a few].

The prerequisites for reading this text are minimal. Only a basic knowledge of measure theoretic probability and Hilbert space theory is assumed. The book is very readable. Proofs are carefully written down and given in every detail, although exercises are not provided.

The treatment starts with a development of martingale theory. Brownian motion is presented as fundamental example of a continuous martingale, followed by an introduction to stochastic integration with respect to continuous martingales. Topics of stochastic analysis relevant to finance as the change of measure technique and martingale representation theorems are presented in detail. The material of the first three chapters is fairly standard and can
be found in many textbooks. I am not that happy with Meyer’s treatment of integration with respect to vector-valued continuous semimartingales, however. This is introduced only as sum of componentwise integrals, a concept of only limited use. Even in a Brownian setting, componentwise stochastic integration is not the right concept in many cases. [Compare example III.4.10 of Jacod and Shiryaev (1987) or the discussion in Chaitlain and Stricker (1994), where the authors stress the relevance of this point for finance.]

In the final chapter, the author turns to applications to finance. After the obligatory Black–Scholes price for an European call option is derived, the general market model is introduced. This is the well-known model where the noise source is a d-dimensional Brownian motion. Basic concepts such as arbitrage or change of numeraire are carefully introduced. However, I miss a discussion of the very basic notion of market completeness. In fact, incomplete models are not treated at all. Having introduced the market model, Meyer turns to the pricing of derivative securities in this framework. Examples like digital options or options to exchange assets are considered. However, American options are not even mentioned. This seems to be a rather serious omission, because in the real world American-style derivatives are by far the most-traded type of options. The last section then is about interest rate derivatives, in the spirit of the so-called “market models.” In particular, Meyer presents valuation formulas in log-Gaussian LIBOR models. Much of the material here can be found in chapters 14–16 of Musiela and Rutkowski (1997).

The bibliography is much too short, containing only 18(!) references. Here the competition is slightly more ahead: for instance, the text of Karatzas and Shreve (1998) has 657 references!

All in all, Continuous Stochastic Calculus With Applications to Finance is carefully written and detailed, but contains only very little new or original material, as the author himself concedes. Thus readers should also take a look at the other books mentioned earlier. However, one interested in a thorough, yet compact introduction into stochastic integration together with a presentation of the very basics in an important application of that theory might take this book into consideration.

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Probability Theory: An Analytic View.
Daniel W. Stroock. New York: Cambridge University Press, 1999. ISBN 0-521-66349-0. xv + 536 pp. $29.95 (P).

Perhaps the most important single question when a new book appears in an established area is: For whom is this book written? Stroock addresses this question in the first paragraph of his Preface, and gives the refreshingly honest answer: himself. The rest of the Preface will reward even the most casual reader with a succinct account of Stroock’s background (the book is dedicated to his teachers Kak, McKean, and Varadhan), and with evidence of a literary merit far beyond that normally found in technical monographs.

The author’s intended audience is indicated in a Foreword, beginning with “This book is intended for graduate students who have a good undergraduate introduction to probability theory, a reasonably sophisticated introduction to modern analysis, and who now want to learn what these two topics have to say about each other.” The book is a goldmine, from which any serious probabilist, whether beginner or greybeard, will benefit, but it is by no means an easy read. This would no doubt be still more so were it not for the moderating influence of Persi Diaconis, gratefully acknowledged: “Persi lobbied for a kinder, gentler book; and for this, my readers owe him a considerable debt of gratitude.” Indeed we do.

Stroock’s natural academic habitat (like that of this reviewer) is the interface between probability and analysis. As he remarks in his Preface, “I am not a dyed-in-the-wool probabilist (i.e., what Donsker would have called a true coin-tosser).” One pleasure the book affords is the chance to place oneself on this probability/analysis scale. (To give a personal view, I consider myself fairly analytical as probabilists go, but less so than Stroock.)

Much of the material is standard enough; the ordering and the treatment are less so and are often highly individual. Chapter I on sums of independent random variables, treats the weak and strong laws and the law of the iterated logarithm. Chapter II is on the central limit theorem, Chapter III treats the Lévy–Khintchine formula and Lévy processes, and Chapter IV treats Wiener measure (Gaussian and Markovian aspects). Conditioning makes an amusing related appearance in Chapter V. Chapter VI on applications of martingale theory, treats (very well) a topic unique to this book at this level, to my knowledge: the Calderón–Zygmund–Stein theory of singular integrals and its relatives in the Burkholder–Gundy theory of martingales, martingale transforms, and so forth. This is perhaps the book’s most distinctive chapter; its attractions to probabilists is its insights (e.g., Paley–Wiener theory) into the singular integral–martingale interface and, to statisticians, its relevance to wavelets (not mentioned in the book). Chapter VII is on martingales and diffusions, with the Stroock–Varadhan martingale problem approach unobtrusively informing the treatment. Chapter VIII is on potential theory, both classical and (to a lesser extent) probabilistic.

One could carp at the selection, ordering, or treatment of some material. I prefer not to; the author declares his hand openly and honestly in advance, and the individuality of his choice is a strength rather than a weakness. What irritated me most was the use of v−1 in place of v throughout, and the use of footnotes rather than a bibliography for references. But these are quibbles. This is a fine book, which will well reward the considerable effort needed to read it.

A number of distinguished probabilists have written one-volume single-author books on probability at the graduate level (Billingsley, Breiman, Chung, Dudley, Kallenberg, and Shiryaev, to name but the first six who come to mind). The challenge for those seeking to join this distinguished company is to write comparably well and to say something new and distinctive—to be individual, without being too idiosyncratic. Stroock succeeds here admirably, and it is a pleasure to see this fascinating book now available in paperback, so that the author’s many admirers can buy their own copy.

Anthony Atkinson and Marco Riani. New York: Springer, 2000. ISBN 0-387-95017-6. xvi + 328 pp. $79.95.

This book presents and develops a new method for “robust” regression and related data analysis. Because the book is based on the author’s “forward search” method, the usefulness of the book depends on the usefulness of the method. The basic idea is as follows. Based on a robust fit to the data, a p point subset is chosen as the starting subset. With very high probability, this subset of the data will not contain any outliers. With minimal assumptions, the least squares (LS) estimator will fit these p points exactly. The next step is to add one additional point to the starting p points. The point that increases the error sum of squares for the p points the least is added. Next, the LS fit to the p + 1 points is computed. Then the residuals for the entire dataset are evaluated at the LS fit to the p + 1 points. The p + 1 points with smallest sum of squared residuals determine the first iteration (from p to p + 1 points) of the forward search methods. Iterations continue in the same way until all n points have been selected. The authors develop a series of plots based on each iteration, for example, the subset size on the x-axis and the sum of squared residuals on the y-axis. A more complicated plot has the same x-axis, but the scaled residuals for each data point on the y-axis. Of course, such a plot would not be useful