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The use of Bayesian methods in financial research

Abstract

Empirical finance research has been aided by the growth of readily available databases and researchers have provided a wealth of evidence regarding market efficiency, pricing, and the role of information that is useful to both analysts and investors. With this growth, however, has been the growth in sample sizes that, in many cases, result in statistical significance where there is little or no economic significance. The authors demonstrate this problem using a sample of stock splits. Though methods such as Bayesian analysis that mitigate this large-sample bias are available, most finance researchers do not apply these methods but instead use samples that approach the actual population in the search for significance.

This paper investigates the use of Bayesian analysis in financial research over the last forty-two years. Bayesian analysis is distinguished from classical statistics by the concept of inverse probability: the authors use information about past events to predict future events. The differences between Bayesian and classical statistics make Bayesian methods especially appropriate for finance applications. Bayesian methods are especially appropriate for applications where subjectivity may lead researchers to inadvertently misrepresent findings or to be influenced by their own preconceived notions. Despite increased interest in Bayesian methods since the mid-1990's and evidence that research using Bayesian method is published most frequently in finance's top research journals, use of Bayesian methods in finance research decreased in the early years of this century.

Keywords: Bayesian analysis, classical statistics.
JEL Classification: C11.

Introduction

In many empirical finance studies the sample sizes are very large. It is quite usual to find empirical studies with 2,000, 5,000 or more observations. Sample selection criteria may be such that, for example, the returns for all stocks traded on the NYSE, AMSE and NASDAQ are included. Or, the sample may be comprised of all the firms listed in Standard & Poor's Compustat database. Why is this a problem? Isn't a large sample more reliable and more powerful?

When using classical statistical tests, with a large enough sample and a fixed level of significance we can reject any null hypothesis. As Stephen Zilaik and Deirdre McCloskey point out in their analysis of empirical studies that appeared in the *American Economic Review*, "… at high sample sizes, after all s/√N approaches zero, all hypotheses are rejected, and in mathematical fact, without having to look at the data, you know they will be rejected at any pre-assigned level of significance"[1]. In other words, as the sample size increases, the test becomes so powerful that the estimated parameter will be found to be significantly different than the hypothesized value even if the actual difference is trivial[2,3]. There is, therefore, a risk that the researcher is drawing the conclusion of statistical significance in the absence of economic significance.

Consider a simple example in which the sample mean abnormal return is 0.5 percent and the sample standard deviation is 9 percent. Suppose we wish to test whether the abnormal return is 0 percent. In most applications, a 0.5 percent abnormal return may not be economically significant, but if we choose our sample size to be sufficiently large, we will be able to conclude that this difference is statistically significant. Table 1 shows the impact of sample size on statistical significance. In the first case, we would fail to reject the null hypothesis of no excess returns. In the third case, the large sample size results in a powerful test and rejection of the null hypothesis. We have "achieved" statistical significance by increasing the sample size.

Table 1. Example of sample size and statistical significance with mean of 0.5% and sample standard deviation of 9.0%

Sample size	Test statistic	Power of the test
30	0.304	6.1%
1,000	1.757	41.0%
3,000	3.043	86.1%

To demonstrate further, consider the example of a simple event study on the event of declaring a stock dividend split. We develop a sample using the following selection criteria:

- Stock dividend or split that is, effectively, a distribution of 50 percent or more.
- Distribution declared between 1990 and 2006.

[1] Ziliak and McCloskey (2004, p. 540).
[2] McCloskey and Ziliak (1996).
[3] As Paul Meehl conjectures, "In nonexperimental settings with large sample sizes, the probability of rejecting the null hypothesis of nil group differences in favor of a directional alternative is about 0.50" (Meehl, 1978).

- Declarer's common stock traded on the NYSE, AMSE or Nasdaq.
- Available beta excess returns and standard deviation excess returns on the Center for Research in Security Prices database for the period ten trading days prior to the event day and ten trading days following the event day.

These selection criteria result in a sample of 1,888 stock dividends and splits. We report the mean excess returns and tests of significance of these means in Table 2. The null hypothesis of no excess returns is rejected for most of the days leading up to, including, and following the event day.

Table 2. Excess returns on sample of 1,888 forward stock splits, between 1990 and 2006, for each trading day from 10 days prior to the declaration date through 10 days following the declaration date

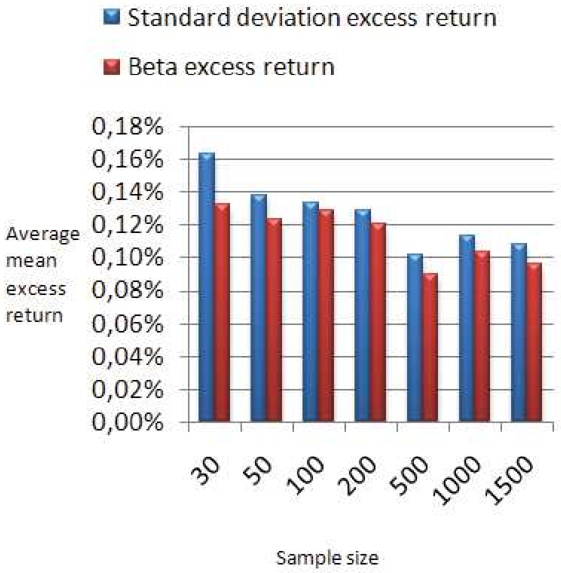
Trading day relative to declaration date	Excess return	Standard deviation excess returns	Beta excess returns
-10	0.0014*	0.0019*	0.0019*
-9	0.0015*	0.0022*	0.0019*
-8	0.0012*	0.0019	0.0016
-7	0.0014*	0.0019	0.0018
-6	0.0016*	0.0016*	0.0018*
-5	0.0008	0.0011*	0.0010*
-4	0.0019*	0.0024*	0.0023*
-3	0.0018*	0.0023*	0.0021*
-2	0.0023*	0.0028*	0.0026*
-1	0.0019*	0.0024*	0.0023*
0	0.0121*	0.0125*	0.0125*
1	0.0052*	0.0057*	0.0057*
2	0.0028*	0.0032*	0.0031*
3	0.0008	0.0010	0.0012
4	0.0003	0.0006	0.0006
5	0.0004	0.0008	0.0009
6	0.0005	0.0009	0.0009
7	0.0000	0.0000	0.0000
8	0.0007	0.0011*	0.0010*
9	0.0009	0.0011*	0.0010*
10	0.0005	0.0010	0.0008

Note: *Indicates excess return is different from zero at a five percent level of significance.

Looking at this same event, but drawing random samples of specific sizes, produces an interesting finding: increasing the sample size increases the reliability to a point, but large sample sizes result in a rejection of the null hypothesis for even small, economically insignificant excess returns. In other words, we find significance when none is likely. We show this in Figure 1 for the declaration day excess returns. In Panel A of this figure, we show the mean excess return averaged across a sample of sixty stock split events for different sample sizes. In Panel B, we show the proportion of the samples with significant mean excess returns.

From Figure 1 it is evident that if the sample size is large enough, we are much more likely to conclude that the event affects security returns. We obtain this result despite the fact that the mean excess return is smaller for the larger sample sizes and despite the fact that the excess return is, on average, less than ten basis points.

Panel A. Mean excess returns for 60 replications of different sample sizes



Panel B. Proportion of significant excess returns for 60 replications of different sample sizes

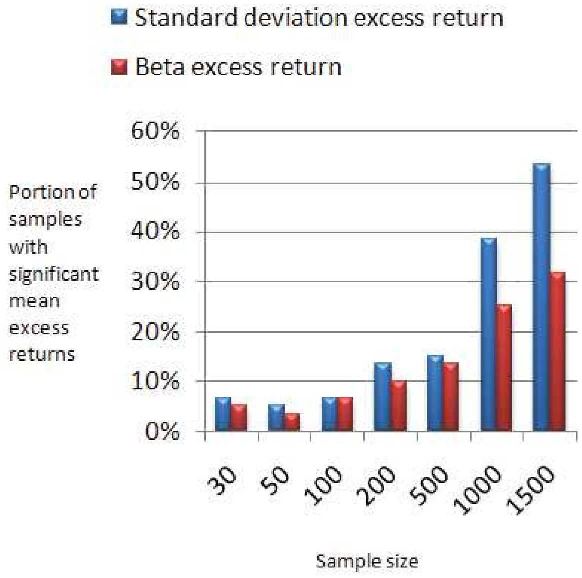


Fig. 1. Results of drawing sixty samples of various sizes from the 1,888 stock splits occurring between 1990 and 2006

1. Bayesian vs. classical statistics

A good illustration of the difference in test conclusions between classical and Bayesian methods are the two articles by Robert Connolly on the weekend effect in security returns[1]. In 1989 Connolly examines unusual stock returns over weekends using classical techniques, testing the hypothesis of equal returns across days of the week using methods common to previous research on this topic. He finds several violations of classical statistical assumptions in the standard methodology and that the results of previous studies on the weekend effect are sensitive to the estimation method and the sampling period. In 1991 he re-examines the weekend anomaly with Bayesian posterior-odds analysis. In this latter study he observes that outliers account for much of the evidence of systematic negative Monday returns. The difference in the results of these two studies is due to reliance on posterior odds rather than on standard F-tests based on fixed significance levels. In this case, the sample sizes are very large so classical tests are biased toward rejecting the null and posterior odds toward favoring the null hypothesis.

Klaas Baks, Andrew Metrick and Jessica Wachter provide an example of incorporating prior information that would be ignored in a classical statistical test[2]. They analyze mutual fund performance from the investor's perspective and examine investors' choices among a risk-free asset, index funds, and actively managed funds. They argue that classical statistical methods have insufficient power to distinguish between the hypothesis that a mutual fund manager has no skill and close alternatives, such as a low level of skill. Using a Bayesian method of performance evaluation and incorporating a range of prior beliefs about managerial skill and fees, they find that in some cases in which investors hold a prior belief that mutual fund managers have a low level of skill, investors make economically significant investments in actively-managed mutual funds.

2. What is Bayesian analysis?

Bayesian inference originated with the writings of the Reverend Thomas Bayes as an alternative to classical probability. Reverend Bayes wrote an essay on the topic which was discovered and published in 1763, two years after his death, and largely ignored for a century[3]. He suggested the concept of inverse induction: rather than calculating the probability of some specific outcome, we can look at the outcomes and make inferences about the likelihood of the causes. In other words, we work toward the probability based on our empirical observations. Bayes' ideas were refined and formalized in the nineteenth century but did not have a significant influence on statistical methodology until the second half of the twentieth century[4]. We can find uses of Bayes' theorem in many different types of applications, including diagnostic medical testing, genetics, and spam filters.

We distinguish Bayesian analysis from classical statistics by the premise that deductive logic alone is not sufficient for inference. In classical hypothesis testing researchers do not learn from the testing process. Instead, they must react to new information by starting over with a new hypothesis, which violates the basic tenets of classical hypothesis testing. Bayesian statisticians, on the other hand, maintain that empirical evidence is used as the basis for revising probabilities not as the basis for determining them in the first place. Bayesian methods allow researchers to update their hypotheses/beliefs before proceeding with testing. Thus, Bayesian analysis allows the researcher to learn from experience. Classical statistics assumes prior ignorance, whereas Bayesian methods permit the use of prior probabilities and, hence, learning.

Though Reverend Bayes did not actually write what had become known as Bayes' theorem, he did provide the logic of this theorem. Bayesian inference combines a prior probability determined from initial information with a likelihood function derived from new data to calculate a posterior probability. The posterior probability is essentially the weighted average of the likelihood and the prior probability. The familiar Bayes' theorem is written as:

$$Posterior\ probability = \frac{(Likelihood)(Prior\ probability)}{Marginal\ likelihood}$$

or, considering two events, A and B:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)},$$

where $P(A|B)$ is the probability of A, conditional on B; $P(B|A)$ is the probability of B, conditional on A; $P(A)$ is the prior belief of the probability of A; and $P(B)$ is the unconditional probability of B.

The researcher may repeat the process of combining the prior probability with the data, continually revis-

[1] Connolly (1989; 1991).

[2] Baks, Metrick and Wachter (2001).

[3] Reverend Bayes' essay was edited by Richard Price and published in 1763 in the *Philosophical Transactions of the Royal Society of London*.

[4] Consistent with the increased interest in Bayesian methodology in the mid-1990s, the Chartered Financial Analyst (CFA®) program added problems requiring Bayes' Rule to examinations in the late 1990s.

ing the probabilities given new information. The posterior probability, therefore, depends on both the prior information and the sample information. As the sample information grows, the information it provides begins to outweigh the prior information. Therefore, two researchers with vastly different priors could arrive at the same conclusion as sample information increases and the posterior probability becomes more concentrated about the true value of the parameter.

Another benefit of using Bayesian techniques is that a researcher can include extraneous information before commencing a test; in fact, all relevant evidence may be included in the prior probability. Different levels of risk aversion, or different priors regarding expected return, therefore, could be incorporated into the analysis. This information is ignored by the researcher using classical statistical methods.

We often describe Bayesian statistics as employing subjective rather than objective probability[1]. Finance may be even more susceptible to subjectivity than the hard sciences because of the behavioral and psychological aspects of financial decisions. In addition, financial data is generated in the market rather than in experiments so researchers cannot control the experimental environment. Further, many finance parameters, such as correlations among stocks' returns, are not stable and are affected by shocks to the system. Bayesian methodology lends itself to this type of data because the opportunity to update the prior belief throughout the empirical study is not only possible, it is fundamental. Using Bayesian methods makes the investigative process dynamic.

Despite its potential value to finance research and application, the use of Bayesian methods in financial research is not wide-spread. Do finance researchers ignore sample size issues? Mostly, yes. We highlight a few of the applications of Bayesian methods to finance issues in Table 3.

Table 3. Examples of studies in finance using Bayesian methods

Topic	Study
Asset allocation	Herold and Maurer (2003)
Asset pricing	Pastor (2000), Pastor and Stambaugh (2000), (2001)
Estimation of the equity premium	Bossaerts (2001)
Examination of mutual fund performance	Pastor and Stambaugh (2002)
Foreign exchange	Bos, Mahieu, and van Dijk (2000), Joseph (2001), Garratt, Psaradakis and Sola (2001)
Market efficiency	Bondarenko and Bossaerts (2000)
Market microstructure	Jamal and Sunder (2001)
Modeling of stock return volatility	Avramov (2002)
Portfolio analysis	Aguilar and West (2000), Polson and Tew (2000)
Prediction of stock returns	Brav (2000)
Time varying returns	Watanabe (2000), Neely and Weller (2000)

3. How often is Bayesian analysis used in finance research?

Bayesian inference has been applied in economics and finance since Bayes' theorem gained in popularity in the 1800s[2]. For example, Alfred Cowles used Bayes' theorem in his 1933 analysis of stock market forecasting ability[3].

To better understand the use of Bayesian inference in finance, we examine articles in 87 finance, economics, and statistics journals for Bayesian-related finance applications published from 1960 through 2004. We provide a list of the journals that we reviewed in Appendix.

We identify 885 articles that pass our initial screen of mentioning Bayesian analysis. However, not all of these articles using Bayesian terminology actually use Bayesian methods; many use the language of Bayesian inference without actually using the methodology[4]. We removed articles that did not actually apply Bayesian methods from our collection[5]. Other surveys of Bayesian applications such as Poirier (2006) do not screen for actual application of Bayesian methodology as rigorously.

Though we searched journals beginning in 1960, there were no articles using Bayesian methods in any journal from 1960 to 1967, and no articles using Bayesian methods in 36 journals from 1968 to 2004.

[1] Press and Tanur (2001) argue that Bayesian methods may replace some of the classical, frequentists' statistical methodology. They argue that even the most successful scientists sometimes have misrepresented findings or have been influenced by their own preconceived notions or the beliefs of their mentors.

[2] Warren Persons provides an historical overview of the application of statistical approaches in economics from the 18th century through the first quarter of the 20th century (Persons, 1925).

[3] Cowles (1933).

[4] For example, some articles passed our initial screen because they discussed prior beliefs, but did not actually apply Bayesian inference. Some studies claim to use Bayesian methodology when, in fact, they do not. Other papers refer to Bayesian reasoning or Bayesian methodology, reference a paper using Bayesian methods, or suggest a Bayesian extension.

[5] Papers deemed to be primarily economics or statistics papers, for example, were not included in the sample. Initial and final reference lists are available upon request.

Our final collection of articles includes 496 articles appearing in 51 journals from 1968 to 2004. We conclude that the use of Bayesian analysis is infrequent during that period.

Most of the uses of Bayesian analysis in these journals appear in the leading journals. Consider the leading academic journals in finance: *Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, and the *Journal of Financial and Quantitative Analysis*. In the 1990-2004 period, the proportion of papers that employed any type of Bayesian analysis is generally quite low, with Bayesian analysis absent in many years for several journals, as we show in Figure 2.

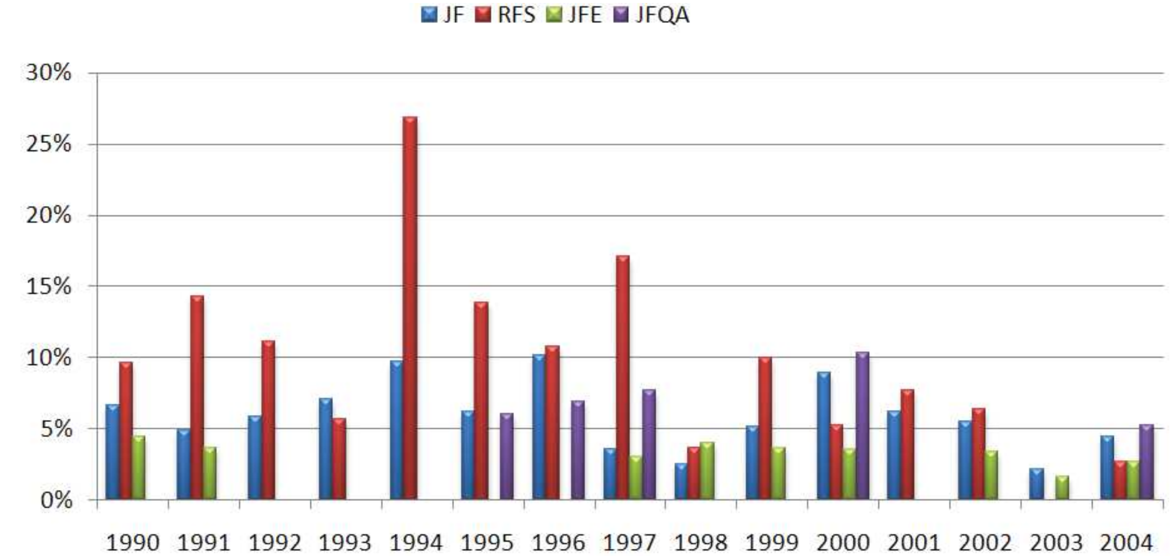


Fig. 2. Proportion of articles in the top four academic finance journals that include Bayesian analysis

Breaking down the collection of articles by journal, we see that the *Journal of Finance* published 27 percent of the Bayesian applications, followed by the *Review of Financial Studies* with 11.5 percent and the *Journal of Financial and Quantitative Analysis* with 10 percent. In other words, the studies using Bayesian analysis are concentrated primarily in a few journals.

The first articles using Bayesian methods in the *Journal of Finance* appeared in 1972. We show the percent of articles using Bayesian methods published in the *Journal of Finance* by year in Figure 3.

It appears that the *Journal of Finance* led the Bayesian trend: the *Journal of Finance* published the majority of the early Bayesian applications in finance and then led the decrease in Bayesian publications. Although the *Journal of Finance* dominates with regard to the number of publications utilizing Bayesian methods, Bayesian methods have never dominated the *Journal of Finance*. Bayesian applications represent ten percent or less of the articles in any issue of *Journal of Finance* over the 1972-2004 period.

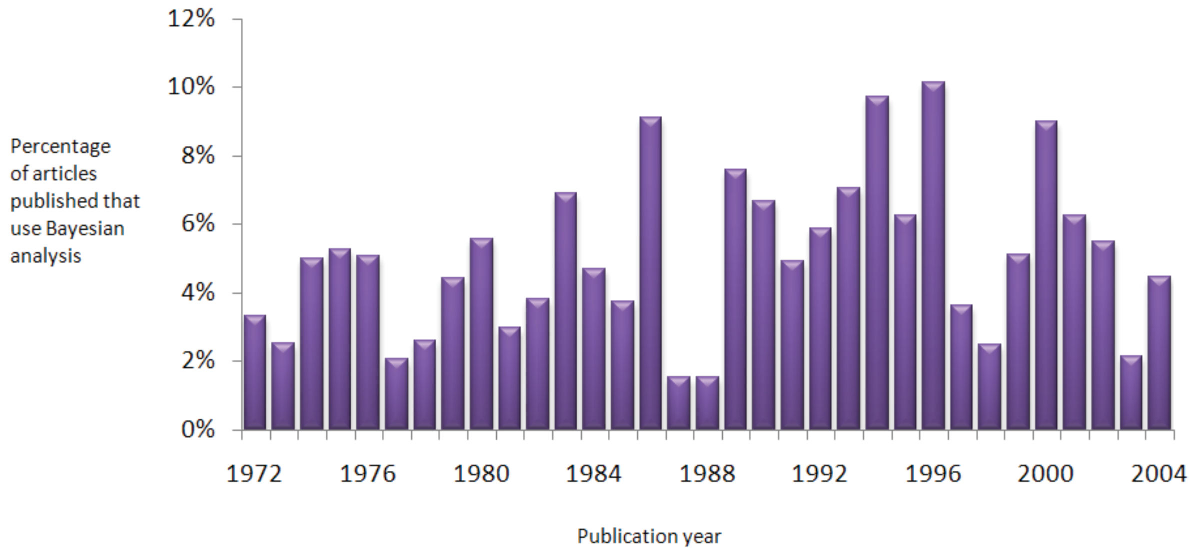


Fig. 3. Percentage of articles in the *Journal of Finance* that use Bayesian analysis

Bayesian methods have been applied to a wide variety of research issues in the field of finance. We classify the publications in Table 4 by topic. Most of the applications involve asset pricing, portfolio analysis, time-varying returns, market efficiency, and market microstructure[1]. No topic dominated the Bayesian applications in any particular year, although portfolio analysis shows the most consistency over the years.

Table 4. Distribution of articles using Bayesian analysis by topic, 1968-2004

Rank	Topic	Frequency
1	Market efficiency studies	67
2	Asset pricing, including CAPM, APT, and cross-sectional return predictability	65
3	Time varying returns, including examining return distributions and predictability	44
4	Portfolio analysis and performance	42
5	Derivatives	29
6	Market microstructure, including the effects of different market structures on returns	25
7	Foreign exchange and purchasing power parity	19
8	Financial intermediaries and markets, including studies on the banking system and flow of funds	15
9	Other corporate topics	14
10	Financial contracting and agency cost papers exploring alternative managerial compensation methods and their effectiveness at reducing agency costs	11
11	Mergers and acquisitions	10
12	Capital structure effects of debt usage on returns and firm value	7
13	Behavioral finance	7
14	Dividend policy	5
15	Technical analysis	3
	Other topics, each with frequency equal to one	12

Conclusion

In our look at the use of Bayesian analysis in finance research, we find that even though studies using Bayesian methods appear in finance's top journals, Bayesian analysis is not applied in enough of the research in which it would be useful. One problem with classical statistical analysis when it is applied in finance research is that it does not consider the learning from the research process. Further, the large samples used in many empirical analyses make it too easy for researchers to find a statistically significant result even though this result may not be economically significant. Bayesian methods avoid the dangers inherent in large sample sizes.

It is possible that the decrease in the use of Bayesian methods is just a temporary lull and that the use of Bayesian analysis could have a resurgence in the finance discipline. Bayesian analysis is picking up steam in statistics and the hard sciences and making its way into other disciplines[2], the methods and models are being refined, and dedicated Bayesian software is now availabe[3]. Finance researchers will be running out of excuses for not using Bayesian analysis.

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[1] Looking closely at the researchers and research that involves Bayesian statistics, we see that the research is dominated by Robert Stambaugh, Lubos Pastor, Christopher Barry, David Easley and Maureen O'Hara.

[2] Berger (2000) indicates that the use of Bayesian statistics in the statistics discipline has not seen a decline.

[3] Although several Bayesian software packages have been developed (e.g. *Bayesian Analysis, Computation and Communication* (BACC), *MathWorks* Statistics Toolbox "slicesample" function, and BFRM), BUGS and SAS currently dominate. The BUGS Project refers to *Bayesian Inference Using Gibbs Sampling* (BUGS), which led to WinBUGS and OpenBUGS. SAS/STAT software provides two macros (bayestests, bayesintervals) and three procedures (GENMOD, LIFEREG, and PHREG).

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Appendix

Table 1A. Journals examined for articles employing Bayesian analysis

Accounting and Finance	Journal of Banking Research
Applied Financial Economics	Journal of Corporate Finance
Applied Financial Economics Letters	Journal of Derivatives
Applied Mathematical Finance	Journal of Economics and Finance
Advances in Financial Education	Journal of Empirical Finance
Advances in Futures and Options Research	Journal of Finance
Advances in Financial Planning and Forecasting	Journal of Financial Economics
Advances in Investment Analysis and Portfolio Management	Journal of Financial Econometrics
Advances in International Business and Finance	Journal of Financial Education
Advances in Financial Economics	Journal of Financial Engineering
Advances in Mathematical Program and Financial Planning	Journal of Financial Intermediation
Advances in Pacific Basin Business, Economics and Finance	Journal of Fixed Income
Advances in Pacific Basin Financial Markets	Journal of Futures Markets
Advances in Quantitative Analysis of Accounting and Finance	Journal of Financial Markets
Advances in Working Capital Management	Journal of Financial and Quantitative Analysis

Table 1A (cont.). Journals examined for articles employing Bayesian analysis

Asia-Pacific Financial Markets	Journal of Financial Research
Derivatives Quarterly	Journal of Financial Statement Analysis
European Finance Review	Journal of Financial Services Research
European Financial Management	Journal of International Financial Management and Accounting
European Journal of Finance	Journal of International Financial Markets, Institutions and Money
Financial Analysts Journal	Journal of International Money and Finance
Financial Management	Journal of Investing
Financial Markets, Institutions and Instruments	Journal of Money, Credit and Banking
Financial Practice and Education	Journal of Multinational Financial Management
Financial Review	Journal of Portfolio Management
Finance Research Letters	Journal of Risk Finance
Finance and Stochastics	Journal of Small Business Finance
Financial Services Review	Mathematical Finance
Global Finance Journal	Managerial Finance
International Finance	Multinational Finance Journal
International Finance Review	Pacific Basin Finance Journal
International Journal of Finance	Quarterly Review of Economics and Finance
International Journal of Finance and Economics	Recent Developments in International Banking and Finance
International Journal of Theoretical and Applied Finance	Review of Derivatives Research
International Review of Economics and Finance	Review of Financial Economics
International Review of Finance	Review of Futures Markets
International Review of Financial Analysis	Review of Financial Studies
Journal of Accounting, Auditing and Finance	Research in Financial Services
Journal of Applied Corporate Finance	Research in Finance
Journal of Applied Finance	Research in International Business Finance
Journal of Alternative Investments	Research of Finance
Journal of Business	Review of Pacific Basin Financial Markets and Policies
Journal of Banking and Finance	Review of Quantitative Finance and Accounting
Journal of Business Finance and Accounting	