Bayesian Probability and Statistics in Management Research : A New Horizon

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Journal of Management 2013 39: 5 originally published online 17 October 2012
DOI: 10.1177/0149206312463183

Journal of Management
Vol. 39 No. 1, January 2013 5-13
DOI: 10.1177/0149206312463183

Call for Papers

Bayesian Probability and Statistics in Management Research: A New Horizon

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Special Issue Purpose

This special issue is focused on how a Bayesian approach to estimation, inference, and reasoning in organizational research might supplement—and in some cases supplant—traditional frequentist approaches. Bayesian methods are well suited to address the increasingly complex phenomena and problems faced by 21st-century researchers and organizations, where very complex data abound and the validity of knowledge and methods are often seen as contextually driven and constructed. Traditional modeling techniques and a frequentist view of probability and method are challenged by this new reality.

Keywords: *Bayes, Bayesian, probability, statistics, research methods, philosophy of science, frequentist*

Background

Since probability in its modern form emerged in the 1600s, it has had two faces (Hacking, 2006). They are often called frequentist and Bayesian (Fienberg, 2006). There is a long history of debate among philosophers, scientists, and statisticians over which is better suited for estimation and inference (Efron, 2005, 2010; Gigerenzer, 1987, 1993; Good, 1989; Little, 2006). However, history shows that both types of probability used to exist harmoniously to solve problems. For example, Gauss and Laplace used the central limit theorem (frequentist) *and* posterior probabilities (Bayesian) to justify aggregating observations with the method of least squares (Stigler, 1986). Unfortunately, beginning in the mid-1800s, the distinction between frequentist and Bayesian probability became divisive (Daston, 1994, 1995), with continued wrangling in the 20th century (Howie, 2002) as Fisher and other statisticians popularized frequentist methods, such as null hypothesis significance testing (NHST; Aldrich, 2008; Danziger, 1994; Gigerenzer, Swijtink, Porter, Daston, Beatty, & Krüger, 1989; MacKenzie, 1981; Zabell, 1989). Organization science researchers followed the path of most other quantitative social sciences and adopted the frequentist approach to probability in the latter half of the 20th century. The adoption was wholesale, so that today quantitative research in the organization sciences relies on *p* values, maximum likelihood (ML) estimation, and other frequentist statistical tools. Although frequentist methods are capable of answering certain types of questions, a "Bayesian revolution" is currently under way in statistics and elsewhere. Indeed, Bayesian analysis finds widespread use in a sweeping array of scientific disciplines, such as physics, chemistry, biology, computer science, genetics, bioinformatics, atmospheric science, and economics. To date, however, the organization sciences have hardly participated in or evaluated the benefit of the Bayesian revolution.

Research Tracks

With this history in mind, the special issue is open to three distinct, yet related, tracks that constellate around Bayesian *estimation*, *inference*, and *reasoning* in organizational research. To assist contributors, we provide some thoughts and ideas within each track, but the call for papers is certainly not limited to only these ideas.

1. Theoretical or empirical work describing Bayesian estimation and inference to address and answer organizational/management research questions.

Today, statisticians often use both Bayesian and frequentist techniques for estimation and inference (Efron, 2005, 2010; Little, 2006), and there are many situations where both techniques are useful and can inform one another (see Bayarri & Berger, 2004; Berger, 2003; Berger, Boukai, & Wang, 1997; Berger, Brown, & Wolpert, 1994; Selke, Bayarri, & Berger, 2001). Contrasting or combining frequentist and Bayesian estimation and inference can provide a useful conceptual understanding of the plurality of probability in organizational research, and, practically speaking, it leads to developing (and learning how to develop and be open to) a more versatile statistical toolbox for organizational researchers.

Bayesian methods allow answering questions about parameters and models directly: "What is the probability of a set of research-relevant parameters, hypotheses, or statistical models *given* the observed data?" Frequentist estimation and inference with NHST answer the "inverse" type of question: "What is the probability of the data *given* what are often research-irrelevant parameters specified by the null hypothesis?" (Berger & Selke, 1987; Kruschke, 2010a, 2010b, 2011). In other words, Bayesian techniques condition on data that are viewed as fixed to determine a distribution of possible parameters; frequentist techniques condition on parameters that are viewed as fixed to determine a distribution of possible data that are never empirically observed (Wagenmakers, Lee, Lodewyckx, & Iverson, 2008). Organizational researchers should understand the research conditions under which Bayesian and frequentist questions and answers are more (and less) useful.

Bayesian estimation and inference have many advantages (Kadane, 1995): rich diagnostic information about parameters and models; controlling for multiple comparisons as a function of the data; handling low-frequency, unbalanced, missing data; and exploration of prior assumptions about model parameters. Also, instead of focusing on Type I and Type II errors, Bayesian thinking places the focus on whether or not parameters and models are sensible for a set of data (e.g., credibility intervals instead of confidence intervals), rather than whether a specific "correct" model has been specified or a null model is rejected (Howson & Urbach, 2006). This is related to the ability to conduct interim analyses or types of "sequential analysis" (see Howson & Urbach, 2006), which in some research contexts can literally save lives (e.g., Cheng & Madigan, 2010). Organizational researchers should understand how all of these factors could influence the decision between frequentist and Bayesian methods.

Organizational and management researchers will benefit from greater exposure to Bayesian methods and software (e.g., Mplus, R packages, WinBUGS, JAGS, Analytica), the practical issues faced when taking a Bayesian approach (e.g., model identification, the stability of parameter estimates, choosing priors in good faith), and strategies and materials for reporting and publishing Bayesian research (e.g., useful templates for tables and graphs). Zyphur and Oswald (2012) provide an introduction to these issues, but more work is needed for explaining the statistical methods and software that are available, along with relevant and useful examples. In addition to a tutorial of the logistics, practicalities, and examples of conducting Bayesian analysis, the special issue is also interested in papers that address *when* or *why* a particular Bayesian technique or logical approach might work best in a certain organizational research context. Such papers should address questions pertaining to data, models, audiences, contexts in which results will be communicated and used, and other key factors that determine the validity and legitimacy of any statistical methods for estimation and inference. For example, how Bayesian methods could be used for graduate education or for bridging the academic–practitioner divide would be of interest.

2. **Empirical management research that features specific types of Bayesian logic and methods to estimate models that are impossible, difficult, or otherwise inhibited by a frequentist paradigm.**

Bayesian estimation allows for flexible modeling in situations where a traditional frequentist approach is impossible (Efron, 2010). For example, structural equation models (SEM) with many latent and categorical observed variables require high-dimensional integration of a parameter space that cannot be conducted by closed-form ML methods. This problem is overcome with Bayesian methods that take advantage of Markov chain Monte Carlo estimation (Asparouhov & Muthén, 2010; Lee, 2007; Muthén, 2010; Muthén & Asparouhov, in press). Bayesian methods will become increasingly critical for modeling the vast multilevel, multisource, and longitudinal data that are increasingly available to organization researchers.

Furthermore, because Bayesian estimation incorporates existing data *and* prior information (probabilities), researchers can estimate parameters that would be impossible with ML methods (Garrett & Zeger, 2000). For example, underidentified models in SEM—with saturated cross-loadings and residual correlations—can be estimated with Bayesian methods (Muthén & Asparouhov, in press; Zyphur & Oswald, 2012). Other very complex models that cannot be estimated with frequentist statistical tools can be gracefully accommodated using a Bayesian approach.

Another advantage of Bayesian methods is in dealing with information provided by small samples, where statistical power issues make it nearly impossible to support frequentist hypotheses with *p* values, even when researchers find exactly what they have predicted (Howson & Urbach, 2006). Bayesian estimation allows incorporating prior empirical findings and theory into model estimation in a scientifically principled manner (Zyphur & Oswald, 2012). Bayesian methods are useful for investigating the rare but extremely important events that define organizational life in a quantitative manner that builds on past empirical findings and theory.

3. Work based in the history and philosophy of science (HPS), the sociology of scientific knowledge (SSK), and/or the field of science, technology, and society (STS)—focusing on knowledge creation with Bayesian methods in organizational research.

Researchers perform induction every time they make inferences from the particular (e.g., a sample) to the general (e.g., a population and/or other contexts), yet Bayesian and frequentists tend to do this in different ways. Although frequentists may focus on theory/model falsification (e.g., Fisher, 1935a, 1935b; Popper, 1959/2002), Bayesians tend to focus on theory/model confirmation (e.g., Howson & Urbach, 2006; see Lange, 2011; Press, 2010: 217-232). Often, organizational researchers do not rely on statistics and probability for induction or generalization in a logically consistent manner. As elsewhere (see Kadane, 1999), they rely on a hybrid of Fisher's (1935a), Neyman and Pearson's (1933), and Neyman's (1937) logic with *p* values, confidence intervals, and Type I and Type II error rates that result in conceptualizations of scientific rigor and generalizability that are good for certain purposes but also limit methods of inquiry, scientific reasoning, and reflexivity (Gigerenzer, 1993, 2004; Gigerenzer et al., 1989; Gigerenzer & Murray, 1987: 1-28). Discussions from philosophy of science on probability's role in induction abound (e.g., Cox & Mayo, 2009; Mayo & Cox, 2009; Zabell, 2011), and from these discussions it is clear that both Bayesians and frequentists operate with assumptions that are impossible to fulfill (see Hájek, 2009; Howson & Urbach, 2006; Senn, 2011). Organizational researchers would benefit from understanding how incorporating or shifting toward Bayesian methods will lead to different assumptions, and how Bayesian probability and methods can facilitate a capable shift when moving research findings from specific contexts to other domains—perhaps through practice (e.g., Verran, 2001). For guidance on developing "evidence for use," a well-developed framework is by Cartwright (2006, 2007, 2010).

As Ellis (1842: 1) notes, "The theory of probabilities is at once a metaphysical and mathematical science." The philosophies underlying Bayesian and frequentist probability paradigms lack cohesion because they define different realities (see Galavotti, 2005). So-called frequentist probability is sometimes confused with stable propensities of chance setups (e.g., Peirce, 1923/2010; Popper, 1959/2002) but usually means hypothetical long-running frequencies (e.g., Ellis, 1842, 1854; Neyman, 1937; Venn, 1866/2006; von Mises, 1957; see Maher, 2010). Alternatively, "Bayesian" probability can be a degree of rational knowledge or inductive, logical, or evidential support for a proposition or state of affairs (e.g., Bayes, 1763; Carnap, 1950; Jaynes, 2003; Jeffreys, 1939/1998; Keynes, 1921/2008; Laplace, 1774/1986; Shannon, 1948), or it can be a degree of belief in a proposition or state of affairs (e.g., De Finetti, 1931/1989; Jeffrey, 2004; Ramsey, 1926/1990; Savage, 1954; see Galavotti, 2011). We are interested in how the ontologies and epistemologies of each can affect the way management researchers conceptualize organizations and their members, as well as intervene in existing organizational practices and enact different organizational realities (e.g., Hacking, 1983; Latour, 2004; Law, 2004; Shapin & Schaffer, 1985).

Statistics and probability involve social practices that structure and legitimize ways of measuring, understanding, and interacting (Gephart, 2006)—statistics and probability are necessary for the modern world to operate as it currently does (Hacking, 1990; Howie, 2002; Porter, 1986). How statistics and probability bring with them a "style of reasoning" (Hacking, 1992, 2002: 159-199) and practices that define organizations and organization science is of interest. An SSK/STS lens would be helpful to understand how statistics and probability work in both management research and organizations, and how pluralizing probability could usefully change organizational research.

To these ends we encourage (although do not require) cross-disciplinary perspectives and collaborations among management researchers, statisticians, and probability theorists, as well as scholars from HPS and SSK/STS.

As is the case for all contributions to *Journal of Management*, papers should offer conceptual and/or empirical insights that substantially advance the organizational literature.

A Caveat

Given the difficult history of probability and statistics (see Daston, 1995; Howie, 2002), we will not entertain papers whose sole purpose is to lambaste null-hypothesis significance testing or frequentist probability more generally. Instead, the special issue is more concerned with *when and in which contexts* adopting Bayesian techniques and logic will provide theoretical and practical benefits for organizational researchers as a complement or alternative to frequentist methods. The special issue also welcomes papers that connect with the many other disciplines developing and using Bayesian methods, whether that is through multidisciplinary collaboration, by drawing analogies with the Bayesian methods employed in other disciplines, or through other means.

Further Reading

For introductions to Bayesian estimation and inference, see Muthén (2010), Muthén and Asparouhov (in press), and Zyphur and Oswald (2012), who in turn provide references to more technical work (e.g., Gelman, Carlin, Stern, & Rubin, 2003; Gill, 2007). From a philosophy of science perspective, the edited volume by Gabbay, Hartmann, and Woods (2011) and Bandyopadhyay and Forster (2011) provide comprehensive introductions; Howson and Urbach (2006) give thorough pro-Bayesian arguments; Hacking (2001) provides a very accessible overview of probability and inductive logic; Maher (2010) provides an online, and opinionated, perspective; and Galavotti's (2005, 2011) work is quite developmental. From a historical and sociological perspective, we recommend the work of Hacking (1990, 1992, 2002, 2006) as well as pieces by Danziger (1994), Daston (1995), Gigerenzer and colleagues (1989), Howie (2002), MacKenzie (1981), Porter (1986), and Stigler (1986) and two edited volumes by Krüger, Daston, and Heidelberger (1987) and Krüger, Gigerenzer, and Morgan (1990).

Deadlines and Submission Instructions

Please submit your papers online via the *Journal of Management* manuscript submission website (http://mc.manuscriptcentral.com/jom), and please indicate that the work is intended for this special issue. **Papers may be submitted any time, up until December 15, 2013. Papers will be reviewed immediately upon submission. JOM averages a 40-day decision window. Papers that are accepted for publication will be immediately produced as discoverable in press papers and distributed ahead of print. No submissions will be reviewed after December 15, 2013**. Please be sure to follow the Submission Guidelines (http://www.sagepub.com/journalsProdDesc.nav?crossRegion=nAmerica&prodId=Journal201724&crossRegion=antiPod#tabview=manuscriptSubmission) as well as the JOM Style Guide (http://www.sagepub.com/upm-data/46742_JOM_Style_Guide_Revised_2011.pdf). Papers will be reviewed following the regular *Journal of Management* double-blind review process.

More Information

Please contact the Special Issue Editors for additional information, for feedback on a proposed topic or study, and to volunteer to review or recommend reviewers for this special issue:

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