Applied Bayesian Modeling for Social Scientists

From theory to estimation and inference

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Course website: umich.instructure.com and jkarreth.net/bayes-icpsr.html (with links to course materials)
Course meetings: June 15–19, 2020 / 9:00am–5:00pm (core course time; asynchronous options available)

Due to Covid-19, this short course will run in a virtual format in 2020.
Participants can access all course information on umich.instructure.com.

Course description and goals

This short course provides an applied introduction to Bayesian data analysis and inference, geared toward participants from the social sciences. Bayesian methods have rapidly grown in the social sciences in recent years and have become a central tool for a wide variety of analytical methods, such as multilevel and measurement models, quantitative text analysis, and network analysis. The goal of this course is to enable participants to immediately use Bayesian tools in their own research and to effectively communicate their Bayesian results to other social science scholars.

Covering both Bayesian theory and applications, the course explores the following topics:

- Why use Bayesian inference?
- Philosophical and theoretical foundations for Bayesian inference
- The mechanics of MCMC tools and sampling
- Building and estimating Bayesian linear and generalized linear models
- Using MCMC output for postestimation, including marginal effects and predicted probabilities
- Bayesian multilevel/hierarchical models
- Bayesian approaches to measurement
- Bayesian tools for model comparison
- Model presentation and communication
- Optimal solutions for workflow and reproducibility

Upon completion of this course, participants will be able to:

- Understand the origins and logic behind Bayesian inference
- Use Bayesian methods for analyzing continuous and categorical outcomes in a regression framework
- Use Bayesian methods for measurement models
- Communicate Bayesian estimation results to practitioners and social science audiences

To allow participants to take full advantage of Bayesian data analysis in their own work, the course also teaches participants how to use the free and open-source software packages R and Stan. Practical examples and applied exercises form an integral part of the course.

Remote Learning Setup

We are using the University of Michigan's Canvas platform to facilitate remote learning. All materials, meetings, and communication will go through Canvas.

To recreate the in-person experience as much as possible, I will create virtual labs as frequent opportunities for hands-on work and immediate feedback from me. Lectures will run interactively on Zoom. Participants can interrupt and ask questions any time. I will also be available for virtual office hours during every day of the workshop and by appointment. We will agree on a specific schedule after our first meeting, but the general schedule for each day will be as follows—all times Eastern Daylight Time (UTC−4):

- 9:00-9:30: Office hour and warmup with brief discussion questions
- 9:30-10:30: Lecture and discussion
- 10:30-11:00: Break
- 11:00-12:00: Lecture and discussion
- 12:00-12:30: Office hour with discussion questions
- 12:30-1:30: "Lunch" break
- 1:30-2:30: Lecture and discussion
- 2:30-3:30: Lab
- 3:30-3:45: Break
- 3:45-5:00: Office hours with discussion questions and assistance with problem sets

Prerequisites

The course presumes a working knowledge of the linear regression model. Familiarity with probability theory would also be helpful, but is not formally required. Participants without any prior knowledge of statistics should consider a more basic quantitative methods course.

Literature

To follow along the course, participants should have access to one of:

- Jackman, Simon. 2009. *Bayesian Analysis for the Social Sciences*. Chichester: Wiley.
- Gelman, Andrew and Hill, Jennifer. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York, NY: Cambridge University Press.

The following books are recommended as background companions; some of their content will appear throughout this course:

- Congdon, Peter D. 2003. *Applied Bayesian Modelling*. Chichester: Wiley.
- Congdon, Peter D. 2010. *Applied Bayesian Hierarchical Methods*. Boca Raton, FL: Chapman / Hall/CRC.
- Gelman, Andrew et al. 2013. *Bayesian Data Analysis, Third Edition*. Boca Raton, FL: Chapman & Hall/CRC.
- Kruschke, John. 2014. *Doing Bayesian Data Analysis, Second Edition: A Tutorial with R, JAGS, and STAN*. Oxford: Academic Press / Elsevier.
- Lunn, David et al. 2012. *The BUGS Book: A Practical Introduction to Bayesian Analysis*. Boca Raton, FL: Chapman / Hall/CRC.
- Ntzoufras, Ioannis. 2009. *Bayesian Modeling Using WinBUGS*. Hoboken, NJ: Wiley.

As a general primer for R, I recommend:

- Fox, John and Weisberg, Sanford. 2011. *An R Companion to Applied Regression, Second Edition*. Thousand Oaks: Sage.
- Teetor, Paul. 2011. R Cookbook. Sebastopol, CA: O'Reilly Media.

As a background guide for mathematical concepts discussed in this short course, I recommend:

- Moore, Will H. and Siegel, David A. 2013. *A Mathematics Course for Political and Social Research*. Princeton, NJ: Princeton University Press.

Additional readings will be made available to participants during the course.

Software and Preparation

Before the start of the course, participants should try to install the following programs on their laptops:

1. R is an open-source software package and available for download at `http://www.r-project.org`. Install the most recent version of R (4.0.0 or higher).
2. RStudio is a convenient integrated development environment for R and available for free at `http://www.rstudio.com`. Install version 1.3 or higher.

We will go over how to use these programs on the first day of the course, using a detailed tutorial with step-by-step instructions.

During the workshop, we will use some packages required for Bayesian analysis in R, including Stan, a powerful and fast-growing tool for Bayesian estimation. To install Stan, you can follow the instructions at `https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started`. But we've set time aside to go over installation during a course unit, since this might require a few individual adjustments depending on your computer's operating system.

Course outline

The following time slots and topics may be modified as the course proceeds. The most current version of this document can be found at `http://www.jkarreth.net/bayes-icpsr.html` and on Canvas.

- **Lectures** are self-contained mini-units mixing lecture and discussion, with video recordings distributed and saved on Canvas.
- **Labs** are guided tutorials with documented scripts available in the course folder. We will work through labs during Zoom meetings.
- **Assignments** are problem sets that participants may complete to reinforce the material learned in the course on that respective day. I will usually be available for about an hour to help with assignments and answer questions.

Day	Unit	Topic
Monday	Lecture 1	Why use Bayesian inference?
Monday	Lecture 2	Philosophical and theoretical foundations
Monday	Lecture 3	Bayesian versus frequentist inference
Monday	Lecture 4	Review: Probability and distributions
Monday	Lab 1	Introduction to R
Monday	Assignment 1	R exercises
Tuesday	Lecture 5	Priors
Tuesday	Lecture 6	The mechanics of MCMC and sampling
Tuesday	Lecture 7	Building and estimating Bayesian (linear) models
Tuesday	Lab 2	Introduction to Stan and rstanarm
Tuesday	Assignment 2	Linear regression
Tuesday	Lecture 8	Convergence diagnostics
Tuesday	Lab 3	Assessing convergence
Wednesday	Lecture 9	Bayesian estimation for binary outcomes
Wednesday	Assignment 3	Binary logit/probit regression
Wednesday	Lecture 10	Using MCMC output for postestimation
Wednesday	Lab 4	Working with MCMC output
Wednesday	Lectures 11–13	Bayesian estimation for ordered, categorical, and count outcomes
Wednesday	Assignment 4	Postestimation for binary logit/probit regression
Thursday	Lab 5	Writing customized models in Stan
Thursday	Lecture 14	Bayesian linear multilevel models
Thursday	Lecture 15	Bayesian multilevel models for non-continuous outcomes
Thursday	Assignment 5	Estimating multilevel models
Friday	Lecture 16	Bayesian approaches to measuring latent variables
Friday	Lecture 17	Bayesian tools for model comparison and model checking
Friday	Lab 6	Communicating results from Bayesian analysis
Friday	Lecture 18	Optimizing workflow for reproducibility

For each day, the core reading usually provides substantial details for the units discussed on that day. Background readings typically address questions you may have during and after course. Sample applications demonstrate the techniques encountered on the respective day.

Day 1 Monday, June 15

Lecture 1 Why use Bayesian Inference?
Lecture 2 Philosophical and theoretical foundations
Lecture 3 Bayesian versus frequentist inference
Lecture 4 Review: Probability and distributions
Lab 1 Introduction to R
Assignment 1 R exercises at the end of Lab 1

Core reading:

- Jackman, chapter 1 & appendix B.

Background:

- Siegfried, Tom. 2010. "Odds are, it's wrong: Science Fails to Face the Shortcomings of Statistics." *Science News* 177 (7): 26–29.
- Senn, Stephen. 2003. "Bayesian, Likelihood, and Frequentist Approaches to Statistics." *Applied Clinical Trials* 12 (8): 35–38.

Day 2 Tuesday, June 16

Lecture 5 Priors
Lecture 6 The mechanics of MCMC tools and sampling
Lecture 7 Building and estimating Bayesian (linear) models
Lab 2 Introduction to Stan and rstanarm
Assignment 2 Linear regression
Lecture 8 Convergence diagnostics
Lab 3 Assessing convergence

Core reading:

- Jackman, chapters 2–5.
- Western, Bruce and Jackman, Simon. 1994. "Bayesian Inference for Comparative Research." *American Political Science Review* 88 (2): 412–423.

Background:

- Gill, Jeff and Walker, Lee D. 2005. "Elicited Priors for Bayesian Model Specifications in Political Science Research." *Journal of Politics* 67 (3): 841–872.
- Seaman, John W. III, Seaman, John W. Jr., and Stamey, James D. 2012. "Hidden Dangers of Specifying Noninformative Priors." *The American Statistician* 66 (2): 77–84.
- Kass, Robert E. and Wasserman, Larry. 1996. "The Selection of Prior Distributions by Formal Rules." *Journal of the American Statistical Association* 91 (435): 1343–1370.
- Efron, Brad. 1986. "Why Isn't Everyone a Bayesian?" *American Statistician* 40 (1): 1–5.
- Robert, Christian and Casella, George. 2010. *Introducing Monte Carlo Methods with R*. New York, NY: Springer, Chapter 8.
- Cowles, Mary Kathryn and Carlin, Bradley P. 1996. "Markov Chain Monte Carlo Convergence Diagnostics: A Comparative Review." *Journal of the American Statistical Association* 91 (434): 883–904.

- Gelman, Andrew and Shirley, Kenneth. 2011. "Inference from Simulations and Monitoring Convergence." Chap. 6 in *Handbook of Markov Chain Monte Carlo*, ed. by Brooks, Steve et al., 163–174. Chapman / Hall/CRC.

Sample applications:

- Blais, André, Guntermann, Eric, and Bodet, Marc A. 2017. "Linking Party Preferences and the Composition of Government: A New Standard for Evaluating the Performance of Electoral Democracy." *Political Science Research and Methods* 5 (2): 315–331.
- Lee, Myunghee and Murdie, Amanda. 2020. "The Global Diffusion of the #MeToo Movement." *Politics & Gender*.

Day 3 Wednesday, June 17

Lecture 9	Bayesian estimation for binary outcomes
Assignment 3	Binary logit/probit regression
Lecture 10	Using MCMC output for postestimation
Lab 4	Working with MCMC output
Lecture 11	Bayesian estimation for ordered outcomes
Lecture 12	Bayesian estimation for categorical outcomes
Lecture 13	Bayesian estimation for count outcomes
Assignment 4	Postestimation for binary logit/probit regression

Core reading:

- Jackman, chapters 6 & 8

Background:

- King, Gary, Tomz, Michael, and Wittenberg, Jason. 2000. "Making the Most of Statistical Analyses: Improving Interpretation and Presentation." *American Journal of Political Science* 44 (2): 347–361.
- Hanmer, Michael J. and Kalkan, Kerem Ozan. 2013. "Behind the Curve: Clarifying the Best Approach to Calculating Predicted Probabilities and Marginal Effects from Limited Dependent Variable Models." *American Journal of Political Science* 57 (1): 263–277.
- Albert, James H. and Chib, Siddhartha. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *Journal of the American Statistical Association* 88 (422): 669–679.
- Hollenbach, Florian M., Montgomery, Jacob M., and Crespo-Tenorio, Adriana. 2019. "Bayesian Versus Maximum Likelihood Estimation of Treatment Effects in Bivariate Probit Instrumental Variable Models." *Political Science Research and Methods* 7 (3): 651–659.
- Gelman, Andrew et al. 2008. "A weakly informative default prior distribution for logistic and other regression models." *Annals of Applied Statistics* 2 (4): 1360–1383.

Sample application:

- Karreth, Johannes. 2018. "The Economic Leverage of International Organizations in Interstate Disputes." *International Interactions* 44 (3): 463–490.
- Stegmueller, Daniel. 2013b. "Modeling Dynamic Preferences: A Bayesian Robust Dynamic Latent Ordered Probit Model." *Political Analysis* 21 (3): 314–333.
- Alvarez, R. Michael and Nagler, Jonathan. 1998. "When Politics and Models Collide: Estimating Models of Multiparty Elections." *American Journal of Political Science* 42 (1): 55–96.

- Lacy, Dean and Burden, Barry C. 1999. "The Vote-Stealing and Turnout Effects of Ross Perot in the 1992 U.S. Presidential Election." *American Journal of Political Science* 43 (1): 233–255.
- Imai, Kosuke and Dyk, David A. van. 2005. "A Bayesian analysis of the multinomial probit model using marginal data augmentation." *Journal of Econometrics* 124 (2): 311–334.
- Martin, Andrew D. 2003. "Bayesian Inference for Heterogeneous Event Counts." *Sociological Methods & Research* 32 (1): 30–63.
- Ghosh, Sujit K., Mukhopadhyay, Pabak, and Lu, Jye-Chyi. 2006. "Bayesian analysis of zero-inflated regression models." *Journal of Statistical Planning and Inference* 136 (4): 1360–1375.
- Neelon, Brian H, O'Malley, A James, and Normand, Sharon-Lise T. 2010. "A Bayesian model for repeated measures zero-inflated count data with application to outpatient psychiatric service use." *Statistical Modelling* 10 (4): 421–439.

Day 4 Thursday, June 18

Lab 5 Writing customized models in Stan
Lecture 14 Bayesian multilevel models for linear outcomes
Lab 6 Estimating multilevel models
Lecture 15 Bayesian multilevel models for non-continuous outcomes

Core reading:

- Gelman & Hill, chapter 17, 18, 19, 24, 25

Background:

- Steenbergen, Marco R. and Jones, Bradford S. 2002. "Modeling Multilevel Data Structures." *American Journal of Political Science* 46 (1): 218–237 (for a refresher on multilevel models).
- Shor, Boris et al. 2007. "A Bayesian Multilevel Modeling Approach to Time-Series Cross-Sectional Data." *Political Analysis* 15 (2): 165–181 (if you work with TSCS data).
- Bell, Andrew and Jones, Kelvyn. 2015. "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data." *Political Science Research and Methods* 3 (1): 133–153 (if you work with TSCS data).
- Plümper, Thomas and Troeger, Vera E. 2019. "Not so Harmless After All: The Fixed-Effects Model." *Political Analysis* 27 (1): 21–45 (if you work with TSCS data).
- Greenland, Sander. 2007. "Bayesian perspectives for epidemiological research. II. Regression analysis." *International Journal of Epidemiology* 36 (1): 195–202 (if you work with more complex nesting structures).
- Gelman, Andrew, Hill, Jennifer, and Yajima, Masanao. 2012. "Why We (Usually) Don't Have to Worry About Multiple Comparisons." *Journal of Research on Educational Effectiveness* 5 (2): 189–211.
- Gelman, Andrew and Pardoe, Iain. 2006. "Bayesian Measures of Explained Variance and Pooling in Multilevel (Hierarchical) Models." *Technometrics* 48 (2): 241–251.

Sample applications:

- Duch, Raymond M., May, Jeff, and Armstrong, David A. 2010. "Coalition-directed Voting in Multiparty Democracies." *American Political Science Review* 104 (4): 698–719.
- Stegmueller, Daniel et al. 2012. "Support for Redistribution in Western Europe: Assessing the Role of Religion." *European Sociological Review* 28 (4): 482–497.
- Martin, Andrew D. 2003. "Bayesian Inference for Heterogeneous Event Counts." *Sociological Methods & Research* 32 (1): 30–63.

- Pang, Xun. 2010. "Modeling Heterogeneity and Serial Correlation in Binary Time-Series Cross-sectional Data: A Bayesian Multilevel Model with AR(p) Errors." *Political Analysis* 18:470–498.
- Pang, Xun. 2014. "Varying Responses to Common Shocks and Complex Cross-Sectional Dependence: Dynamic Multilevel Modeling with Multifactor Error Structures for Time-Series Cross-Sectional Data." *Political Analysis* 22 (4): 464–496.
- Ward, Michael D., Siverson, Randolph M., and Cao, Xun. 2007. "Disputes, Democracies, and Dependencies: A Reexamination of the Kantian Peace." *American Journal of Political Science* 51 (3): 583–601.
- Blaydes, Lisa and Linzer, Drew A. 2012. "Elite Competition, Religiosity and Anti-Americanism in the Islamic World." *American Political Science Review* 106 (2): 225–243.
- Lock, Kari and Gelman, Andrew. 2010. "Bayesian Combination of State Polls and Election Forecasts." *Political Analysis* 18 (3): 337–348.
- Masters, Ryan K., Hummer, Robert A., and Powers, Daniel A. 2012. "Educational Differences in U.S. Adult Mortality." *American Sociological Review* 77 (4): 548–572.
- Stegmueller, Daniel. 2013a. "How Many Countries for Multilevel Modeling? A Comparison of Frequentist and Bayesian Approaches." *American Journal of Political Science* 57 (3): 748–761.
- Chaudoin, Stephen, Milner, Helen V., and Pang, Xun. 2015. "International Systems and Domestic Politics: Linking Complex Theories with Empirical Models in International Relations." *International Organization* 69 (2): 275–309.
- Beazer, Quintin H. and Woo, Byungwon. 2016. "IMF Conditionality, Government Partisanship, and the Progress of Economic Reforms." *American Journal of Political Science* 60 (2): 304–321.
- Danneman, Nathan and Ritter, Emily Hencken. 2014. "Contagious Rebellion and Preemptive Repression." *Journal of Conflict Resolution* 58 (2): 254–279.
- Quaranta, Mario and Martini, Sergio. 2016. "Does the economy really matter for satisfaction with democracy? Longitudinal and cross-country evidence from the European Union." *Electoral Studies* 42:164–174.
- Eagle, David. 2016. "The Negative Relationship between Size and the Probability of Weekly Attendance in Churches in the United States." *Socius* 2.
- Cao, Xun and Ward, Hugh. 2017. "Transnational Climate Governance Networks and Domestic Regulatory Action." *International Interactions* 43 (1): 76–102.
- Helgason, Agnar Freyr and Mérola, Vittorio. 2017. "Employment Insecurity, Incumbent Partisanship, and Voting Behavior in Comparative Perspective." *Comparative Political Studies* 50 (11): 1489–1523.
- Mummolo, Jonathan and Peterson, Erik. 2018. "Improving the Interpretation of Fixed Effects Regression Results." *Political Science Research and Methods*.
- Allen, Michael A. et al. Forthcoming. "Outside the Wire: U.S. Military Deployments and Public Opinion in Host States." *American Political Science Review*.

Day 5 Friday, June 19

Lecture 16 Bayesian approaches to measurement
Lecture 17 Bayesian tools for model comparison and model checking
Lab 7 Communicating results from Bayesian analysis
Lecture 18 Optimal solutions for workflow and reproducibility

Core reading:

- Jackman, chapter 9.

Background:

- On factor models:
  - Lopes, Hedibert Freitas. 2014. "Modern Bayesian Factor Analysis." In *Bayesian Inference in the Social Sciences*, ed. by Jeliazkov, Ivan and Yang, Xin-She, 115–153. John Wiley & Sons, Inc., sections 5.1 and 5.2.
- On IRT models:
  - Jackman, Simon. 2001. "Multidimensional Analysis of Roll Call Data via Bayesian Simulation: Identification, Estimation, Inference, and Model Checking." *Political Analysis* 9 (3): 227.
  - Clinton, Joshua D. and Jackman, Simon. 2009. "To Simulate or NOMINATE?." *Legislative Studies Quarterly* 34 (4): 593–621.
- On model comparison:
  - Jackman, Simon. 2001. "Multidimensional Analysis of Roll Call Data via Bayesian Simulation: Identification, Estimation, Inference, and Model Checking." *Political Analysis* 9 (3): 227.
  - Montgomery, Jacob M. and Nyhan, Brendan. 2010. "Bayesian Model Averaging: Theoretical Developments and Practical Applications." *Political Analysis* 18 (2): 245–270.
  - Vehtari, Aki, Gelman, Andrew, and Gabry, Jonah. 2016. "Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC." *Statistics and Computing*: 1–20.

Sample applications for measurement models:

- Bakker, Ryan. 2009. "Re-measuring Left–Right: A Comparison of SEM and Bayesian Measurement Models for Extracting Left–Right Party Placements." *Electoral Studies* 28 (3): 413–421.
- Bakker, Ryan and Poole, Keith T. 2013. "Bayesian Metric Multidimensional Scaling." *Political Analysis* 21 (1): 125–140.
- Benson, Brett V. and Clinton, Joshua D. 2016. "Assessing the Variation of Formal Military Alliances." *Journal of Conflict Resolution* 60 (5): 866–898.
- Campbell, Susanna P., Findley, Michael G., and Kikuta, Kyosuke. 2017. "An Ontology of Peace: Landscapes of Conflict and Cooperation with Application to Colombia." *International Studies Review* 19 (1): 92–113.
- Caughey, Devin and Warshaw, Christopher. 2015. "Dynamic Estimation of Latent Opinion Using a Hierarchical Group-Level IRT Model." *Political Analysis* 23 (2): 197–211.
- Caughey, Devin and Warshaw, Christopher. 2016. "The Dynamics of State Policy Liberalism, 1936-2014." *American Journal of Political Science* 60 (4): 899–913.
- Clinton, Joshua D. and Jackman, Simon. 2009. "To Simulate or NOMINATE?." *Legislative Studies Quarterly* 34 (4): 593–621.
- Copelovitch, Mark S., Gandrud, Christopher, and Hallerberg, Mark. "Financial Regulatory Transparency and Sovereign Borrowing Costs."
- Fariss, Christopher J. 2014. "Respect for Human Rights has Improved Over Time: Modeling the Changing Standard of Accountability." *American Political Science Review* 108 (2): 297–318.
- Fox, Jean-Paul and Glas, Cees. 2001. "Bayesian Estimation of a Multilevel IRT Model Using Gibbs Sampling." *Psychometrika* 66 (2): 271–288.

- Fox, Jean-Paul and Glas, Cees A.W. 2003. "Bayesian modeling of measurement error in predictor variables using item response theory." *Psychometrika* 68 (2): 169–191.
- Garrett, Elizabeth S. and Zeger, Scott L. 2000. "Latent Class Model Diagnosis." *Biometrics* 56 (4): 1055–1067.
- Gray, Julia and Slapin, Jonathan B. 2012. "How Effective are Preferential Trade Agreements? Ask the Experts." *Review of International Organizations* 7 (3): 309–333.
- Hare, Christopher et al. 2015. "Using Bayesian Aldrich-McKelvey Scaling to Study Citizens' Ideological Preferences and Perceptions." *American Journal of Political Science* 59 (3): 759–774.
- Hollyer, James R., Rosendorff, B. Peter, and Vreeland, James Raymond. 2014. "Measuring Transparency." *Political Analysis* 22 (4): 413–434.
- Linzer, Drew A. and Staton, Jeffrey K. 2015. "A Global Measure of Judicial Independence, 1948-2012." *Journal of Law and Courts* 3 (2): 223–256.
- Manatschal, Anita and Bernauer, Julian. 2016. "Consenting to Exclude? Empirical Patterns of Democracy and Immigrant Integration Policy." *West European Politics* 39 (2): 183–204.
- Rosas, Guillermo, Shomer, Yael, and Haptonstahl, Stephen R. 2015. "No News Is News: Nonignorable Nonresponse in Roll-Call Data Analysis." *American Journal of Political Science* 59 (2): 511–528.
- Selin, Jennifer L. 2015. "What Makes an Agency Independent?" *American Journal of Political Science* 59 (4): 971–987.
- Slapin, Jonathan B. and Proksch, Sven-Oliver. 2008. "A Scaling Model for Estimating Time-Series Party Positions from Texts." *American Journal of Political Science* 52 (3): 705–722.
- Treier, Shawn and Jackman, Simon. 2008. "Democracy as a Latent Variable." *American Journal of Political Science* 52 (1): 201–217.
- Juhl, Sebastian. Forthcoming. "Measurement Uncertainty in Spatial Models: A Bayesian Dynamic Measurement Model." *Political Analysis*.
- Caughey, Devin, O'Grady, Tom, and Warshaw, Christopher. Forthcoming. "Policy Ideology in European Mass Publics, 1981–2016." *American Political Science Review*.
- Juhl, Sebastian. 2019. "Measurement Uncertainty in Spatial Models: A Bayesian Dynamic Measurement Model." *Political Analysis* 27 (3): 302–319.
- Claassen, Christopher. 2019. "Estimating Smooth Country–Year Panels of Public Opinion." *Political Analysis* 27 (1): 1–20.
- Claassen, Christopher. 2020. "Does Public Support Help Democracy Survive?" *American Journal of Political Science* 64 (1): 118–134.
- Williams, Rob et al. Forthcoming. "A latent variable approach to measuring and explaining peace agreement strength." *Political Science Research and Methods*.
- Kenwick, Michael R. 2020. "Self-Reinforcing Civilian Control: A Measurement-Based Analysis of Civil-Military Relations." *International Studies Quarterly* 64 (1): 71–84.
- Solis, Jonathan A. and Waggoner, Philip D. 2020. "Measuring Media Freedom: An Item Response Theory Analysis of Existing Indicators." *British Journal of Political Science*.

Sample applications for model comparison:

- Montgomery, Jacob M. and Nyhan, Brendan. 2010. "Bayesian Model Averaging: Theoretical Developments and Practical Applications." *Political Analysis* 18 (2): 245–270.
- Warren, T. Camber. 2014. "Not by the Sword Alone: Soft Power, Mass Media, and the Production of State Sovereignty." *International Organization* 68 (1): 111–141 (skim as an example of an application of BMA).

- Pepinsky, Thomas B. 2014. "The Politics of Capital Flight in the Global Economic Crisis." *Economics & Politics* 26 (3): 431–456 (skim as an example of an application of BMA).
- Raftery, Adrian E. 1995. "Bayesian Model Selection in Social Research." *Sociological Methodology* 25:111–163 (Background on BMA, read if you're interested)
- Gelman, Andrew and Rubin, Donald B. 1995. "Avoiding Model Selection in Bayesian Social Research." *Sociological Methodology* 25:165–173 (Background on BMA, read if you're interested)
- Bartels, Larry M. 1997. "Specification Uncertainty and Model Averaging." *American Journal of Political Science* 41 (2): 641–674 (Background on BMA, read if you're interested)
- Montgomery, Jacob M., Hollenbach, Florian M., and Ward, Michael D. 2012. "Improving Predictions Using Ensemble Bayesian Model Averaging." *Political Analysis* 20 (3): 271–291 (if you are interested prediction & forecasting).
- Cranmer, Skyler J., Rice, Douglas R., and Siverson, Randolph M. 2017. "What To Do About Atheoretic Lags." *Political Science Research and Methods* 5 (4): 641–665 (BMA as an approach to atheoretic lags in regression).