

MODULE SPECIFICATION • ELECTIVE

Bayesian Methods in Econometrics

This course provides an introduction to simulation-based methods that are commonly used in microeconometrics. The emphasis is Bayesian, although posterior analysis is also contrasted with maximum likelihood estimation. Despite the technical content, the course begins with an introduction to the Bayesian paradigm, and introduces key concepts and vernacular.

10 CREDITS	15h CONTACT HOURS	85h PRIVATE STUDY	100h TOTAL STUDY
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COURSE CONVENOR

NAME Dr Lennart Hoogerheide

OFFICE By appointment — please email to arrange a convenient time

COURSE STRUCTURE

Econ 7907 is a 10-credit course and students are expected to input approximately 100 hours of study. The total number of contact hours is 15 hours, leaving 85 hours for private study. Delivery is by lectures — 15 hours across the first three weeks of term, comprising 10 hours of lectures and 5 hours of tutorials. Optional clinics run on the last day of the course.

During private study, balance the course material (the primary source) against the recommended textbooks: think critically about how these fit into the body of knowledge, perform the exercises, complete coursework and revise. You can expect to perform well only by working consistently through the year.

MODULE PROGRAMME

LECT.	TOPIC	SESSION CONTENT
01	Introduction to Bayesian statistics and its differences versus the frequentist approach	- Advantages of the Bayesian approach over the frequentist approach: general theory and simple examples - Bayes' rule: prior density, likelihood, posterior density and posterior density kernel - Informative versus non-informative priors - Bayesian analysis of model with Bernoulli/binomial distribution under uniform prior
02	Prior specification in simple econometric models, Gibbs sampling	- Conjugate priors - Bayesian analysis of model with Bernoulli/binomial distribution under conjugate (beta) prior distribution - Bayesian analysis of model with geometric distribution - Proper versus improper priors - Bayesian analysis of model with normal distribution with known and unknown variance - Markov chain Monte Carlo (MCMC) methods: burn-in, Gibbs sampling method
03	Metropolis-Hastings algorithms: methods and applications in econometric models	- MCMC methods: random walk Metropolis(-Hastings) method, candidate distribution, diagnostic checks, acceptance percentage - Bayesian estimation of (G)ARCH models - Bayesian estimation of Poisson regression model - MCMC methods: independence chain Metropolis-Hastings method, candidate distribution, diagnostic checks, acceptance percentage
04	Posterior model probabilities, normal linear regression model, Bayesian Model Averaging for forecast combination of autoregressive models	- Posterior model probabilities: posterior odds ratio, prior odds ratio, Bayes factor, marginal likelihood - Monte Carlo methods: importance sampling method, acceptance-rejection method - Bayesian analysis of model with normal distribution with unknown variance under flat prior - Bayesian analysis of normal linear regression model under flat prior - Savage-Dickey density ratio for computing the Bayes factor of nested models - Posterior predictive density in autoregressive (AR) models - Bayesian Model Averaging (BMA) for forecast combination - Jeffreys-Lindley-Bartlett paradox and the need for proper priors in BMA
05	Gibbs sampling with data augmentation, hierarchical prior, Jeffreys prior, numerical standard errors	- MCMC methods: Gibbs sampling with data augmentation - Bayesian estimation of a mixture model with known/fixed number of components - Bayesian estimation of a mixture model with unknown/flexible number of components: hierarchical priors, sparse finite mixture - Bayesian estimation of probit, tobit models - Jeffreys prior - Numerical precision of simulation results: numerical standard errors, relative numerical efficiency

KEY SKILLS

By the end of this course, students should have some knowledge and understanding of:

- The basis and motivation for Bayesian Econometrics
- The distinction between inference and estimation in Bayesian versus classical methods
- How to construct posterior distributions of unknown parameters
- The application of Bayesian methods to problems in microeconometrics

DESIRED OUTCOMES

By the end of this course, students should be able to:

- Communicate and present complex arguments in oral and written form with clarity
- Appreciate instances where the application of Bayesian methods is appropriate
- Work with R and/or Python to operationalise Bayesian methods

ASSESSMENT

WEIGHTING	100% coursework
ISSUED	End of week 6
DUE	End of week 10 — four weeks for completion
SUBMISSION	Electronically via the Moodle site for this course
FEEDBACK	Returned within 4 weeks of the deadline, as marker's notes appended to the PDF of your coursework

Marking criteria and penalties are set out in the Economics Undergraduate Handbook and the general course information paper, available via the Current Student page of the university website under Academic Regulations.

COURSE TEXT & RECOMMENDED READING

Copies of the lecture slides are made available on the course web pages, together with additional material and course announcements. The following chapter and textbook can be useful, alongside articles on the topics of the course.

- Hoogerheide, L. F., Van Dijk, H. K. and Van Oest, R. D. (2009). Simulation based Bayesian econometric inference: principles and some recent computational advances. Chapter 7 in Handbook of Computational Econometrics, Wiley & Sons, 215–280
- Koop, G. (2003). Bayesian Econometrics. John Wiley & Sons
- Casella, G. and George, E. I. (1992). Explaining the Gibbs Sampler. The American Statistician 46, 167–174
- Chib, S. and Greenberg, E. (1995). Understanding the Metropolis–Hastings Algorithm. The American Statistician 49(4), 327–335
- Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H. and Teller, E. (1953). Equation of state calculations by fast computing machines. Journal of Chemical Physics 21, 1087–1092
- Tanner, M. A. and Wong, W. H. (1987). The Calculation of Posterior Distributions by Data Augmentation. Journal of the American Statistical Association 82(398), 528–540
- Ardia, D., Hoogerheide, L. F. and Van Dijk, H. K. (2012). A comparative study of Monte Carlo methods for efficient evaluation of marginal likelihoods. Computational Statistics & Data Analysis 56(11), 3398–3414



- Hoogerheide, L. F., Opschoor, A. and Van Dijk, H. K. (2012). A class of adaptive importance sampling weighted EM algorithms for efficient and robust posterior and predictive simulation. *Journal of Econometrics* 171(2), 101–120
- Malsiner-Walli, G., Frühwirth-Schnatter, S. and Grün, B. (2016). Model-based clustering based on sparse finite Gaussian mixtures. *Statistics and Computing* 26, 303–324
- Geweke, J. (1993). Bayesian Treatment of the Independent Student-t Linear Model. *Journal of Applied Econometrics* 8, S19–S40
- Kass, R. and Raftery, A. (1995). Bayes Factors. *Journal of the American Statistical Association* 90(430), 773–795
- Basturk, N., Cakmakli, C., Ceyhan, S. P. and Van Dijk, H. K. (2014). On the Rise of Bayesian Econometrics after Cowles Foundation Monographs 10, 14. Tinbergen Institute Discussion Paper TI 2014–085/III
- Hoogerheide, L. F., Ardia, D. and Corré, N. (2012). Stock Index Returns' Density Prediction using GARCH Models: Frequentist or Bayesian Estimation? *Economics Letters* 116(3), 322–325
- Hoogerheide, L. F., Block, J. H. and Thurik, R. (2012). Family background variables as instruments for education in income regressions: A Bayesian analysis. *Economics of Education Review* 31(5), 515–523