Course Outline:
Bayesian Econometrics
with Applications in Macroeconomics & Finance

Daniel Buncic

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1 Course Details

Lecture Time	:	Tuesday and Friday, 08:15 – 12:00
Lecture Room	:	Various rooms (check the schedule for details)
Course Title	:	Bayesian Econometrics
Course Code	:	5326
Instructor	:	Daniel Buncic, PhD, Professor of Finance, Stockholm Business School, Stockholm University.
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Office Hours	:	by appointment. Send me an email with *'SSE-IBE'* in the header
Course Website	:	www.danielbuncic.com/teaching.html

2 Information about the course

2.1 Course Details

This course offers students an introduction to Bayesian econometric methods widely employed in the empirical macroeconomics and finance literature. Bayesian methods have become the norm for analysing statistical problems in empirical studies, particularly when no closed form likelihoods can be computed or when the information in the available data leads to a likelihood function that is uninformative (or flat) with respect to the parameter(s) of interest.

The goal of the course is to get students proficient in using simulation based Bayesian methods to estimate common macroeconomic and financial models using *"real world"* data. Students will be taught how to implement the techniques that are learned in the classroom, with particular focus given to the estimation of macroeconomic/financial models that can be easily cast into a (conditionally normal) state space form. Once in state space form, standard Bayesian filtering and sampling methods will be used to estimate these models.

Topics : The course will cover the following 4 main topics:

Topic 1: Introduction to Bayesian statistics and econometrics

- Overview of classical and Bayesian views on probability
- Brief review of probability distributions
- Examples of Bayesian statistical models
- Bayesian regression model

Topic 2: Priors, numerical integration and overview of Bayesian sampling algorithms

- The role of priors
- Numerical integration techniques
- PIT and Accept/Reject sampling
- Gibbs sampling
- Metropolis-Hastings sampling

- Importance and adaptive sampling (if time permits)

Topic 3: Outline of state-space models and their use in macroeconomics and finance

- Introduction to state space models and the Kalman filter
- Bayesian estimation of state space models
- Simulation smoothing and Gibbs sampling for state space models

Topic 4: Applications

- Bayesian AR with complex root restrictions, Threshold AR models, TVP AR models
- Bayesian Stochastic volatility models, and various VAR models
- Dynamic Model Averaging and/or Selection (if time permits)
- Markov-switching AR models (if time permits)

2.2 Course literature

The reading material for this course will come from a variety of sources. There are a number of textbook style treatments that are quite good to gain a fundamental understanding and overview of Bayesian statistical/econometric methods (see Koop, 2003 and Chan, Koop, Poirier and Tobias, 2019).[1] However, as it is always the case, there are some sections that are explained better in one book and other sections are better explained in another book. Therefore, it is necessary to utilise a number of different textbooks as references.

We will frequently call on sections and chapters from the following standard Bayesian econometrics textbooks: Koop (2003), Gelman, Carlin, Stern and Rubin (2006), Chan *et al.* (2019), Robert (2007), and Jackman (2009). In addition to these, there are two recent review papers written by Koop and Korobilis (2010) and Del Negro and Schorfheide (2012) that offer an overview of recent advances in Bayesian methods in macroeconomics and finance that will be used towards the end of the course. Other journal articles will be referenced and distributed as required. All the reading material, if not available through the University library, will be distributed on the course website.

A list of the books and articles that are used in the course is given on the last page under the References heading. The corresponding readings for each of the Topics that are going to be covered are listed in the last column of the Weekly Lecture Schedule Table. We will try to stick to this list as much as possible, nevertheless, since teaching and learning speed can vary, the schedule is tentative and therefore subject to change.

2.3 Pre-requisites

The prerequisite for the course is a solid understanding of time series econometrics, particularly AR and VAR models. The course extends and partially builds on the material covered in the Masters course '*Applied Econometric Time Series* (5314)' which is offered in the Spring semester of the year at the University. It is further assumed that students have a good foundation in statistics and are comfortable with the manipulation of probability density functions.

Although there is no official prerequisite for a foundation course in statistics, it is assumed that students are familiar with standard statistical concepts such as random variables, means, variances, covariances, distributions, $p-$values, transforms of random variables and so forth. If students are unsure about these concepts or have simply forgotten them, they should consult the appendices of the above listed textbooks for summaries or quick overviews.

As we are going to use a number of distributions very frequently, I have typed up some commonly used ones in the distributions.pdf file. Other good sources of details about distributions are the appendices of

[1] If you are interested in reading about Bayesian decision theory per se, I would recommend the seminal book by Bernardo and Smith (1994). It covers a lot of interesting material, and does so rigourously.

the books that are listed above, the paper by Leemis and McQueston (2008) which shows the relations between univariate PDFs, as well as the Wikipedia website.

2.4 Computing requirements

Although the course will deal with fundamental Bayesian econometric concepts and derivations, the focus of the course — especially towards the second half of the course — is on the **estimation** of time series models that can be put into a **conditionally normal state space form**. I thus expect students to be competent enough to work independently with a (high level) matrix computing language such as Matlab, R, GAUSS or any other software program of your choice. I will use Matlab throughout the course. Matlab is probably one of the most widely used, most powerful and intuitive high level matrix programming *"languages"* that are used in finance, economics and also in engineering. Matlab is available in the university's computing labs.

One of the assessment items for the course is a replication project that will involve the computation of one of the models that will be outlined in the lectures. Students will thus not be able to pass the course without *getting their hands sticky* on a computer.

2.5 Lectures

I will try to keep the lecture environment as informal and *"student friendly"* as possible, so that students feel comfortable enough to ask (hopefully many) questions that will help deepen and strengthen their understanding of the material that is being taught.

I expect students to go through the readings outlined in the Weekly Lecture Schedule **before** the week's lecture, so that they are prepared when they come to class. Since lecture time is scarce, the focus of the lectures will be on outlining the statistical details necessary to conduct the required econometric analysis and on going through the derivations as carefully as necessary. Although some intuition about why we are performing a particular transformation or how to think about a result that we derive will be provided in the lectures, students will gain additional intuition from the assigned readings.

It should be stressed here that Bayesian econometrics is a huge and rapidly growing field in econometrics. This means that we will not have time to cover every aspect of Bayesian econometrics/statistics, and every detail there is to be covered. This also means that we will not conduct a thorough review of all the building blocks that are needed to have a comprehensive treatment of Bayesian econometrics. We will, therefore, have to cover and introduce some concepts and other important results *"on the fly"*, that is, along the way, as is needed. It may thus happen that a concept or terminology is used without having previously defined or formerly introduced it, so I expect students to ask — or to work out themselves — what is meant.

Note that there are no official lab (or computing) sessions scheduled for this course. Students are, therefore, expected to familiarise themselves independent of class time with the required computing material and use the resources that are provided in the lectures. Introductory material on how to get started with Matlab is available on the course's website.

2.6 Notation

Since we will pool information from different textbooks and articles, it is possible that some differences in notation will arise due to the pooling. I will try to be consistent with the notation (and language) used in the lectures and lecture notes. However, it is inevitable that there will be some inconsistencies that will creep in. I thus ask students to be flexible in the use of the notation. It is much more important to understand the concept and building blocks behind a result that is derived rather than to try to memorise the formulas.

I will (try to consistently) use Greek letters for parameters and will put hats for OLS or MLE ($\hat{\ }$) estimates, bars ($\bar{\ }$) (or overlines in $\LaTeX$) for posterior parameters and a zero subscript (ie., β_0) for prior *hyperparameters*. Note though that some textbooks (as well as papers) use underlines (_) for prior *hyperparameters*, so it may be the case that it will creep up in the notation. I will generally try to use $p(\cdot)$ to denote a density function (without distinction in notation whether it is discrete or continuous density function) and $p(\cdot)$ for prior densities. These may be adapted or modified, depending on what model(s) or references we are using at that time.

3 Course Assessment

3.1 Formal Requirements

In order to pass this course, you must attain a total of at least 50% (ie., 50 out of 100). The total mark is computed as the sum of the two assessment components, which are listed below.

3.2 Assessment Details

What	How much	Due in
Assignment(s)	35%	to be announced
Exam(s)	65%	to be announced
Total	100%	

Details of the assignment(s) will be given during class time. The assignment(s) will consist of hand calculation exercises/simple computational tasks, and a major computational task(s) involving the replication of the results of an academic paper and a presentation. One week will be allocated where students/groups will outline the results (as well as possible problems) of their replication project in a short presentation. Details regarding the final exam will be communicated towards the end of the course.

3.3 Comments on course assessment

The format of the assessment items were designed to maximise the students' learning outcomes. There exist many pedagogical studies that show that a continuous stream of learning is much more efficient and beneficial to students than a short intense period of study, since more course material is retained for a longer period of time after the end of the semester. Also, learning material from lecture notes or a book is less likely to get the students understanding of the topics to a level where these can be independently implemented. The assessment is thus split into two parts rather than a single assessment item, so that students are *encouraged* to study for the course on a weekly basis and are *forced* to put the knowledge that they have gained from the readings and the lecture material into practice by coding up independently some of the models that are studied and by discussing any problems that they have encountered with it. My view is that students will learn more from replicating a paper from scratch than from simply attending lectures and taking exams.

4 Weekly Lecture Schedule

The lecture schedule for this course is as follows. The *'Suggested Readings'* column below gives you a reference list of common textbooks and selected papers in addition to the lecture material. Hopefully you will find this list informative. I have written the lecture notes/slides so that they give you condensed, but still all inclusive and detailed information on the topics that we are going to cover in this course. Although the lecture notes are self-contained, some students may like to read up on some of the material that is listed in the *'Suggested Readings'*. Also, note that there will be some overlap in the topics that are covered in each week.

Table 1: Weekly Lecture Schedule

Duration	Lecture Topic	Suggested Readings
4 Lectures	Overview of the course and Introduction to Bayesian econometrics/statistics and review of common probability distributions. Bayes' theorem, Bayesian updating of information, and Bayesian statistical models. Bayesian statistical models continued and introduction to the Bayesian regression model.	**Topic 1:** Koop (2003) Chapters $1-3$, Hoff (2009) Chapters $1-3$ and 5, Gelman *et al.* (2006) Chapters $1-3$, Greenberg (2008) Chapters $1-3$, Lancaster (2004) Chapter 1.
4 Lectures	More on priors for the Bayesian regression model, review of numerical integration methods, introduction to Bayesian simulation methods, Accept/Reject and Importance sampling. Introduction to Markov Chain Monte Carlo methods, Gibbs sampling, and Metropolis-Hastings sampling.	**Topic 2:** Koop (2003) Chapters $4-5$, Hoff (2009) Chapters 6 and $9-10$, Greenberg (2008) Chapters $5-7$, Lancaster (2004) Chapter $3-4$, Chib and Greenberg (1995), Casella and George (1992), Chib (2012).
4 Lectures	Review/introduction to state space models and the Kalman filter, Bayesian estimation of state space models. Forward Filtering Backward Sampling, Simulation Smoothing, Gibbs sampling for state space models.	**Topic 3:** Hamilton (1994) Chapter 13, Kim and Nelson (1999) Chapter 3, 8, Carter and Kohn (1994), Giordani, Pitt and Kohn (2012), Durbin and Koopman (2002).
4 Lectures	Applications: Bayesian AR(2) model with complex root restrictions, Bayesian Threshold Autoregression. Time varying parameter AR and VAR models. Stochastic volatility models, Bayesian VARs. Dynamic Model Averaging/Selection methodology, etc.	**Topic 4:** Del Negro and Schorfheide (2012), Koop and Korobilis (2010), Giordani *et al.* (2012), Primiceri (2005), Koop and Korobilis (2012), Raftery, Kárný and Ettler (2010).
	Final Exam and student presentations to be advised	

This schedule is tentative and thus subject to change!

References

Bernardo, José M. and Adrian F. M. Smith (1994): *Bayesian Theory*, Wiley Series in Probability and Statistics, John Wiley & Sons.

Carter, Chris K. and Robert Kohn (1994): "On Gibbs sampling for state space models," *Biometrika*, **81**(3), 541–553.

Casella, George. and Edward I. George (1992): "Explaining the Gibbs sampler," *The American Statistician*, **46**(3), 167–174.

Chan, Joshua, Gary M. Koop, Dale J. Poirier and Justin L. Tobias (2019): *Bayesian Econometric Methods, 2nd Edition*, Cambridge University Press.

Chib, Siddhartha (2012): "Introduction to Simulation and MCMC Methods," in *The Oxford Handbook of Bayesian Econometrics*, edited by John Geweke, Gary M. Koop and Herman van Dijk, Oxford University Press, 183–216.

Chib, Siddharta and Edward Greenberg (1995): "Understanding the Metropolis-Hastings algorithm," *The American Statistician*, **49**(4), 327–335.

Del Negro, Marco and Frank Schorfheide (2012): "Bayesian Macroeconometrics," in *The Oxford Handbook of Bayesian Econometrics*, edited by John Geweke, Gary M. Koop and Herman van Dijk, Oxford University Press, 293–389. Available from: https://web.sas.upenn.edu/schorf/files/2017/04/bayesian_macro-pjuc2n.pdf.

Durbin, James and Siem J. Koopman (2002): "A simple and efficient simulation smoother for state space time series analysis," *Biometrika*, **89**(3), 603–616.

Gelman, Andrew, John B. Carlin, Hal S. Stern and Donald B. Rubin (2006): *Bayesian Data Analysis, 2nd Edition*, Chapman and Hall CRC Press.

Giordani, Paolo, Michael Pitt and Robert Kohn (2012): "Bayesian inference for Time Series State Space models," in *The Oxford Handbook of Bayesian Econometrics*, edited by John Geweke, Gary M. Koop and Herman van Dijk, Oxford University Press, 61–124.

Greenberg, Edward (2008): *Introduction to Bayesian Econometrics*, Cambridge University Press.

Hamilton, James D. (1994): *Time Series Analysis*, Princeton University Press.

Hoff, Peter D. (2009): *A First Course in Bayesian Statistical Methods*, Springer Verlag.

Jackman, Simon (2009): *Bayesian Analysis for the Social Sciences*, John Wiley and Sons.

Kim, Chang-Jin and Charles R. Nelson (1999): *State-Space Models with Regime Switching: Classical and Gibbs-sampling Approaches with Applications*, MIT Press.

Koop, Gary and Dimitris Korobilis (2012): "Forecasting Inflation using Dynamic Model Averaging," *International Economic Review*, **53**(3), 867–886.

Koop, Gary M. (2003): *Bayesian Econometrics*, John Wiley and Sons.

Koop, Gary M. and Dimitris Korobilis (2010): "Bayesian Multivariate Time Series Methods for Empirical Macroeconomics," *Foundations and Trends in Econometrics*, **3**(4), 267–358. Available from: http://personal.strath.ac.uk/gary.koop/koop_korobilis_Foundations_and_Trends_2010.pdf.

Lancaster, Tony (2004): *An Introduction to Modern Bayesian Econometrics*, John Wiley & Sons.

Leemis, Lawrence M. and Jacquelyn T. McQueston (2008): "Univariate distribution relationships," *The American Statistician*, **62**(1), 45–53.

Primiceri, Giorgio E. (2005): "Time Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, **72**(3), 821–852.

Raftery, Adrian E., Miroslav Kárný and Pavel Ettler (2010): "Online Prediction under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill," *Technometrics*, **52**(1), 52–66.

Robert, Christian P. (2007): *The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation*, Springer Verlag.