Exam for the lecture

"Econometrics III"

	for st		M.Sc. progra	ammes		
14.02.2023		winter terr	n 2022/2023			
Please use block lette	ers:					
Name: Surname			Vorname: First Name			
Studiengang: Course of study			Name der Universität Name of university (Ba degree)			
Matrikelnummer: Student ID			Hochschulstandort (Bachelor): Place of university (Bachelor's degree)			
Declaration:						
		PLEAS	SE SIGN!!!			
I hereby declar	e that I am able to	be examined.				
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Preliminary rema	rks:					
• Write down you examiner.	ur name and enroli	only the paper pro	ovided by the exam	per sheets provided f niner.	for answers by the	
Problem:	1	2	3	НА	S	
Points earned:						
Grade:						
Kiel,				(Prof. Dr. Kai (Carstensen)	

Examination in Econometrics III (Winter Term 2022/23)

February 14, 2023, 12:00 - 13:00

Preliminary remarks:

- 1. Write your name and enrolment (matriculation) number on every sheet of paper!
- 2. Don't use a pencil!
- 3. The exam is composed by 3 problems. Check your exam for completeness!
- 4. You have 60 minutes in total to answer the exam questions.

Good luck!

Problem 1 (22 credits)

Suppose you would like to model the distribution of grades among master's students at CAU Kiel in WiSe 22/23. For that, you assume that a random sample $y = (y_1, ..., y_N)'$ of exam grades comes from a Pareto distribution with **unknown shape parameter** $\theta > 0$ and known scale k > 0 (lower bound of y_i):

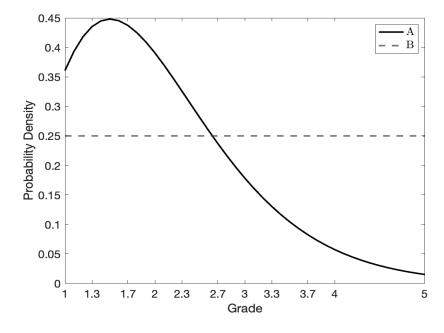
$$p(y_i|\theta, k) = \begin{cases} \theta k^{\theta} y_i^{-(\theta+1)} & \text{if } y_i \ge k\\ 0 & \text{if } y_i < k \end{cases}$$
 (1)

Suppose prior beliefs concerning the **unknown parameter** θ are represented by a Gamma distribution with $p(\theta) \sim G(\mu, \underline{\nu})$:

$$p(\theta) = \left(\frac{\underline{\nu}}{2\mu}\right)^{\frac{\underline{\nu}}{2}} \Gamma\left(\frac{\underline{\nu}}{2}\right)^{-1} \theta^{\frac{\underline{\nu}-2}{2}} \exp\left(-\frac{\theta\underline{\nu}}{2\mu}\right)$$

where $\Gamma(\cdot)$ denotes the Gamma function.

- (a) **(6P)** State the likelihood. *Hint*: to simplify notation, assume that $\left(\prod_{i=1}^{N} y_i\right) = \tilde{y}$.
- (b) **(8P)** Derive the posterior distribution of θ (including posterior parameters). *Hint*: remember the logarithm property $x = \exp(\ln(x))$.
- (c) (2P) Is the Gamma distribution a conjugate prior? Briefly explain!
- (d) (6P) Grades are given on the usual 1-5 scale (from best to worst). Consider two prior distributions A and B for θ which are characterized by the following densities:



Assume you have some information that a large share of students performed very well in the past but you are unsure whether you can trust your source. Which of the above prior specifications (A or B) would you choose? Briefly explain.

Problem 2 (27 credits)

Suppose an estimation problem yields the following bivariate posterior distribution for the two parameters of interest, h_1 and h_2 :

$$p(h_1, h_2|y) \propto h_1^{\frac{\nu-2}{2}} h_2^{\frac{\nu-2}{2}} \exp \left[-\frac{h_1 \nu}{2 \lambda \mu_1} - \frac{h_2 \nu}{2 \mu_2} - \frac{h_1 h_2 \nu}{2} \right],$$

where $h_1 > 0$ and $h_2 > 0$ while $(\underline{\mu}_1, \underline{\mu}_2, \underline{\nu})$ are prior hyperparameters and λ is a known parameter that reflects a prior relationship between h_1 and h_2 .

(a) (12P) Derive the conditional distributions $p(h_1|h_2, y)$ and $p(h_2|h_1, y)$ and show that they are Gamma distributed.

Hint: Remember that the kernel of a Gamma distributed random variable θ follows: $p(\theta) \propto \theta^{\frac{\nu-2}{2}} \exp\left[-\frac{\theta\nu}{2\mu}\right]$, whereas $\theta \sim G(\mu, \nu)$ and $\theta > 0$.

- (b) (8P) Write a pseudo code that applies the Gibbs sampler to find the posterior means of h_1 and h_2 .
- (c) (7P) Assume that λ is now unknown and a nonlinear function such that $\lambda = f(h_1, h_2)$. Which simulation procedure would you use to estimate $E(h_1, h_2|y)$ in this scenario? Explain your choice.

Problem 3 (11 credits)

Consider the M-dimensional VAR(p) model

$$y_t = a_0 + A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t, \qquad t = 1, \dots, T.$$
 (2)

with $\varepsilon_t \sim N(0, \Sigma)$ and $E(\varepsilon_t \varepsilon_s) = 0$ for $t \neq s$.

- (a) (5P) Why is shrinkage particularly important for large VAR models?
- (b) **(6P)** Explain the key elements of the Minnesota prior that makes it appealing for Big Data applications and still allowing for analytical posterior results.