

# Online appendix for “Constrain equilibrium climate sensitivity via Bayesian composite likelihood”

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This appendix shows mixing properties of the Markov chain. The main text reports estimation results but delegates posterior traces, autocorrelation functions, and effective sample sizes of various model parameters here. Notations follow the main text unless stated otherwise.

**Keywords:** *Composite likelihood, Equilibrium climate sensitivity, Energy balance model, Bayesian inference, model averaging*

**JEL Classification:** C11, C22, C51

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Considering there are 31 EBMs estimated in the CL, we report the posterior traces for the model parameters that show the smallest effective sample size among the 31 sets of model parameters.

Mixing quality is measured via inefficiency factor and effective sample size. Inefficiency factor measures the number of autocorrelated posterior draws needed to achieve the same inferential accuracy of random draws. Thus, a smaller inefficiency factor is always preferred. Following the literature, we compute the inefficiency factor of a coefficient  $\vartheta$  by

$$\text{inefficiency factor}(\vartheta) = 1 + 2 \sum_{i=1}^{\infty} \omega_i \rho_i(\vartheta),$$

where  $\rho_i(\vartheta)$  is the  $i$ -th sample autocorrelation function of the posterior draws. We choose Barlett weights for  $\omega_i$ 's.

Effective sample size measures the hypothetical posterior sample size where posterior draws were made randomly. Its approximation can be expressed as the ratio of the posterior size to the inefficiency factor, in percentage point. A larger effective sample size is always preferred.

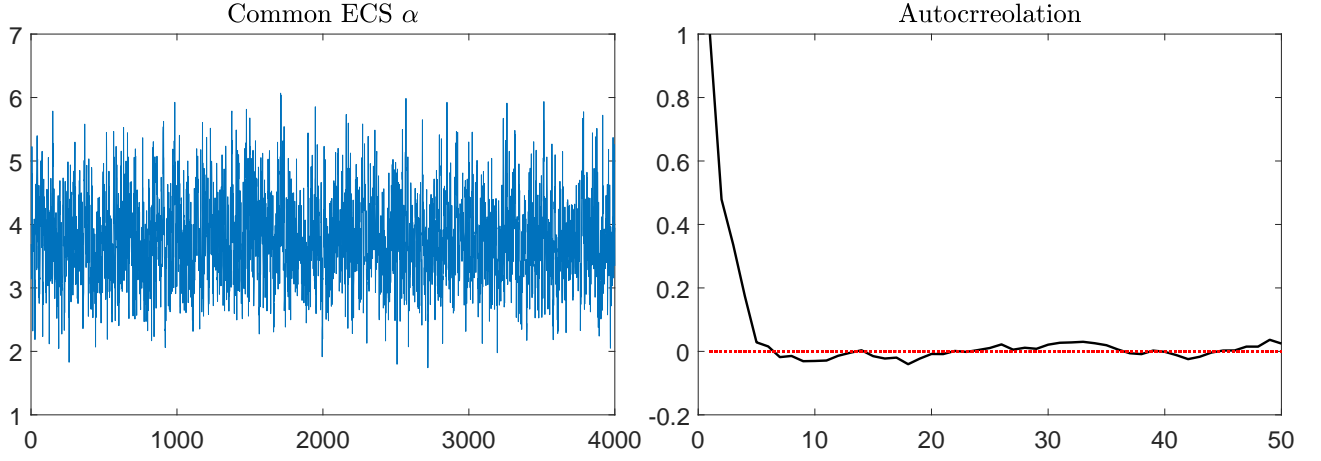


Figure 1: Common ECS  $\alpha$ . Inefficiency factor: 3.67. Effective sample size: 27.25%.

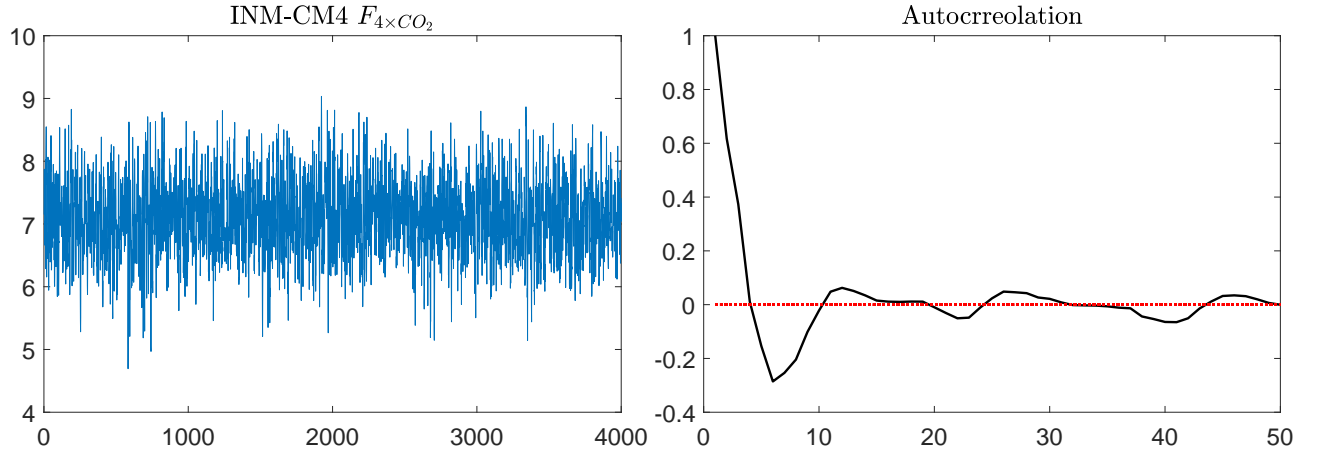


Figure 2:  $CO_2$  forcing  $F_{4 \times CO_2}$ . Inefficiency factor: 6.03. Effective sample size: 16.58%.

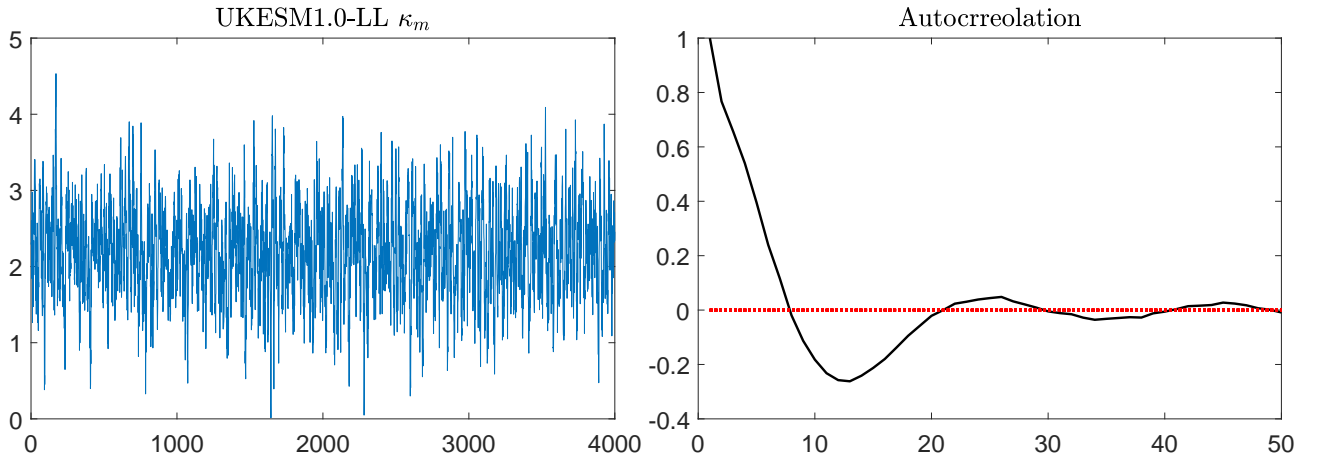


Figure 3: Heat transfer coefficient of the middle ocean layer  $\kappa_m$ . Inefficiency factor: 5.90. Effective sample size: 16.95%.

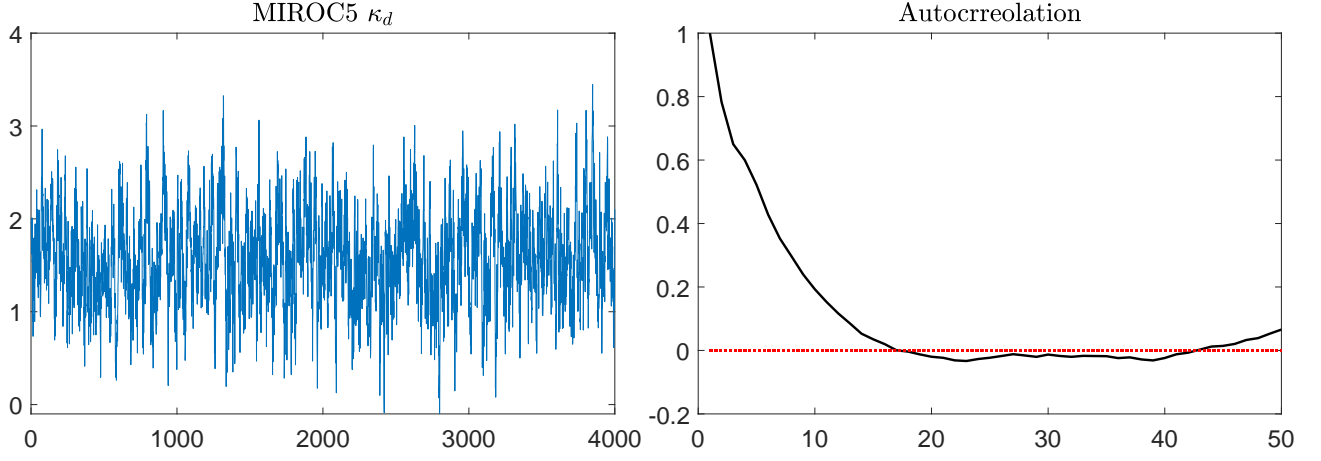


Figure 4: Heat transfer coefficient of deep ocean  $\kappa_d$ . Inefficiency factor: 9.28. Effective sample size: 10.78%.

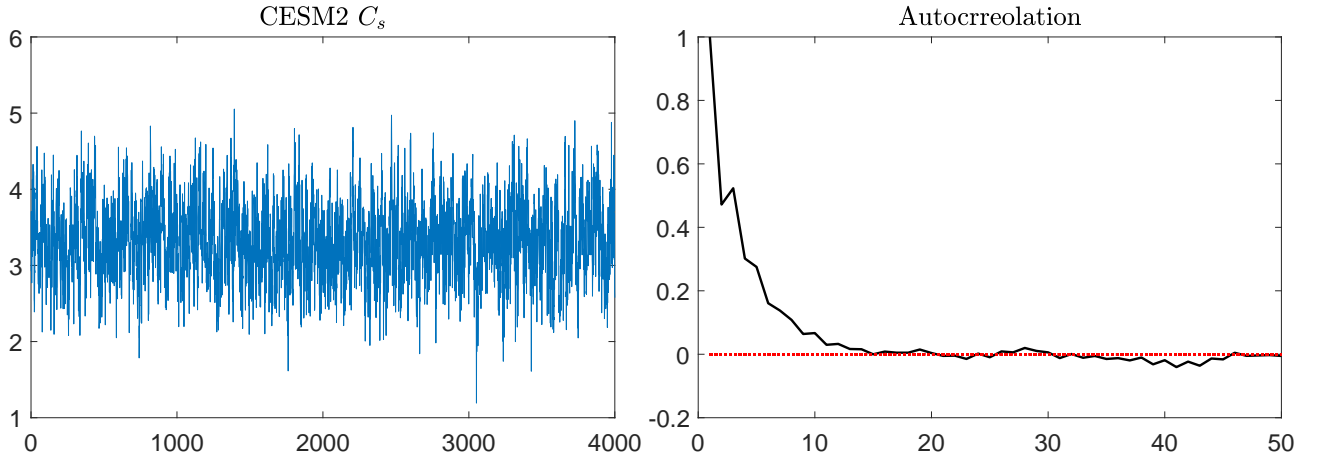


Figure 5: Heat capacity of ocean surface  $C_s$ . Inefficiency factor: 4.55. Effective sample size: 22.00%.

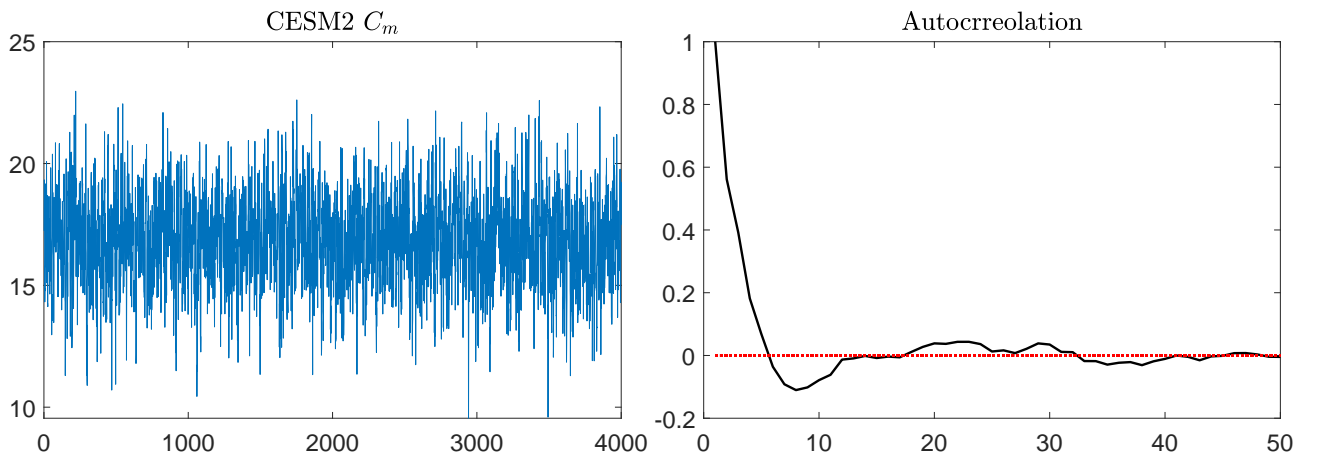


Figure 6: Heat capacity of the middle ocean layer  $C_m$ . Inefficiency factor: 2.25. Effective sample size: 44.44%.

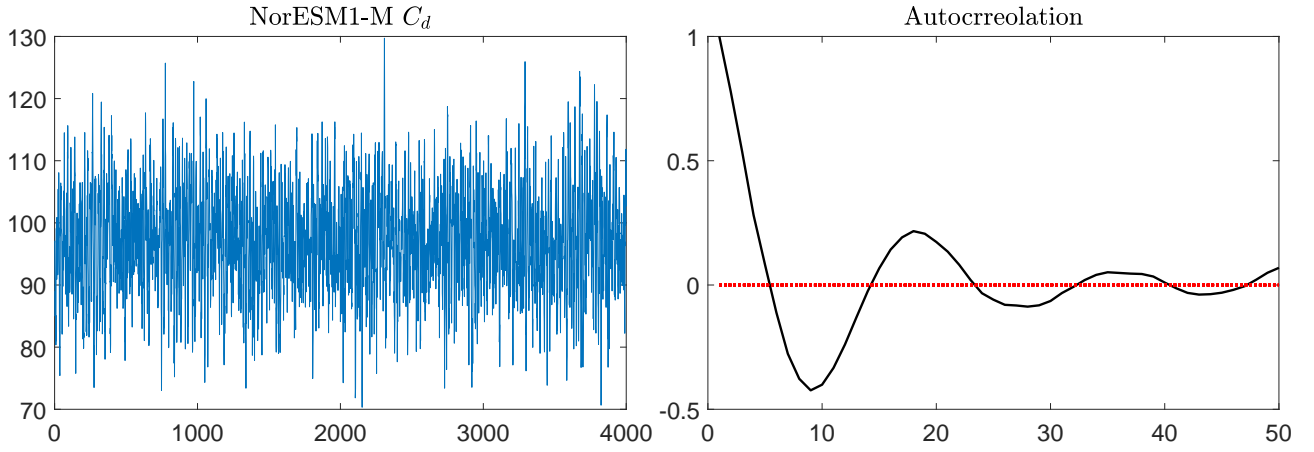


Figure 7: Heat capacity of deep ocean  $C_d$ . Inefficiency factor: 7.40. Effective sample size: 13.51%.

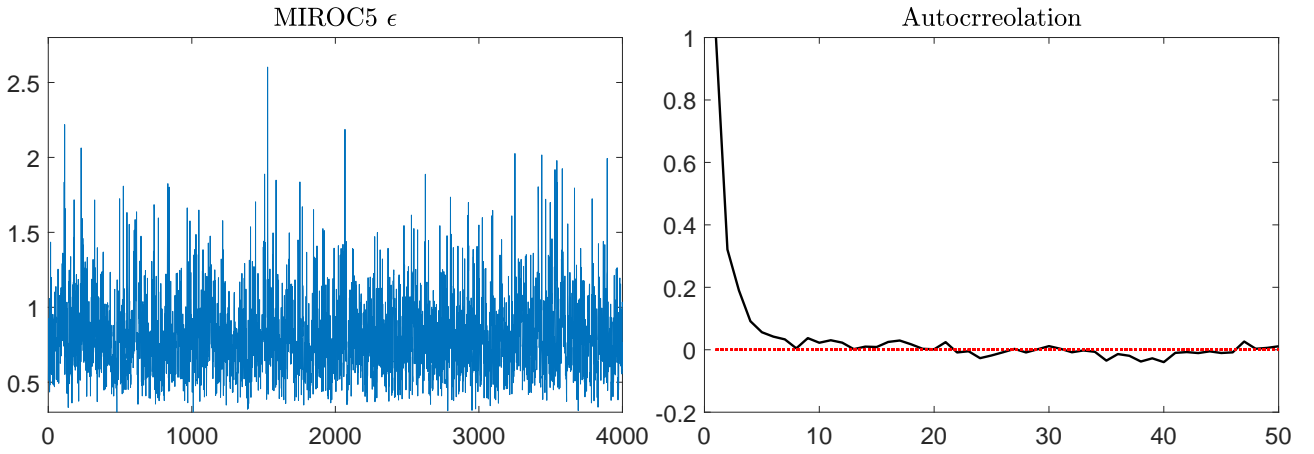


Figure 8: The efficacy coefficient  $\epsilon$ . Inefficiency factor: 3.88. Effective sample size: 25.77%.

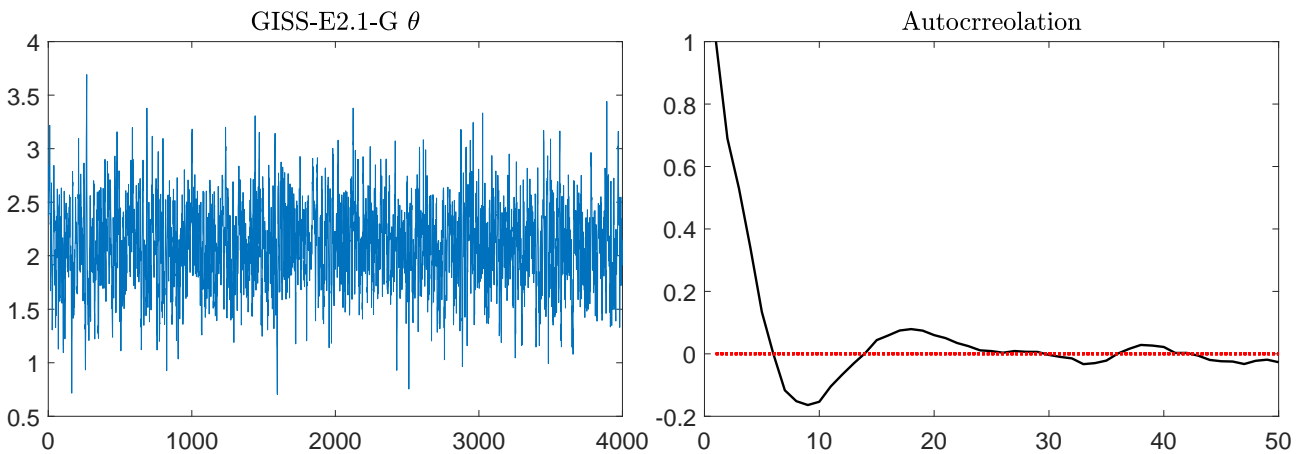


Figure 9: The AR coefficient of the  $\text{CO}_2$  forcing process  $\theta$ . Inefficiency factor: 6.65. Effective sample size: 15.04%.

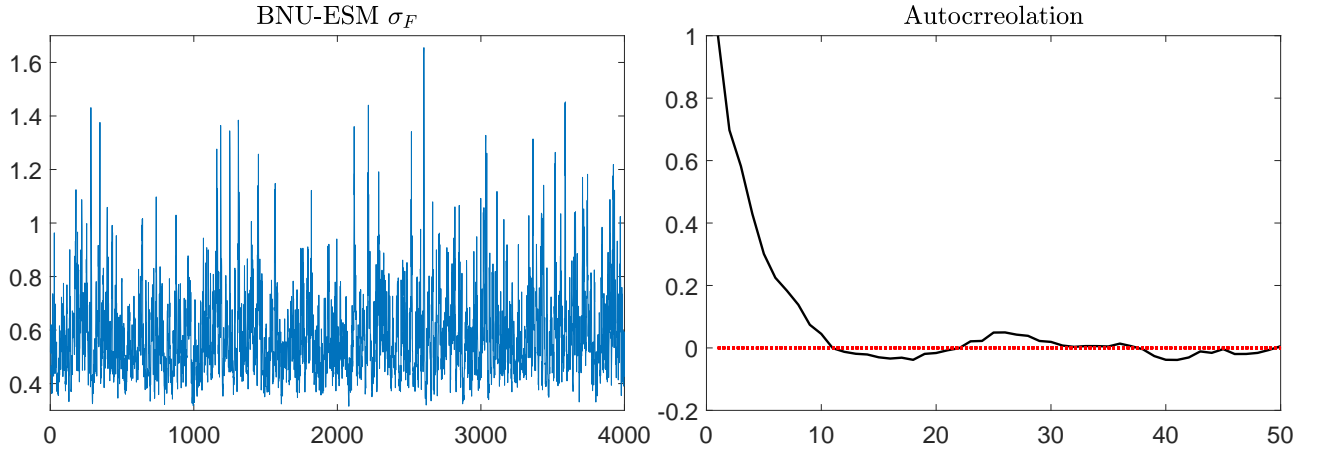


Figure 10: The scaling parameter of the CO<sub>2</sub> forcing process  $\sigma_F$ . Inefficiency factor: 9.30. Effective sample size: 10.75%.

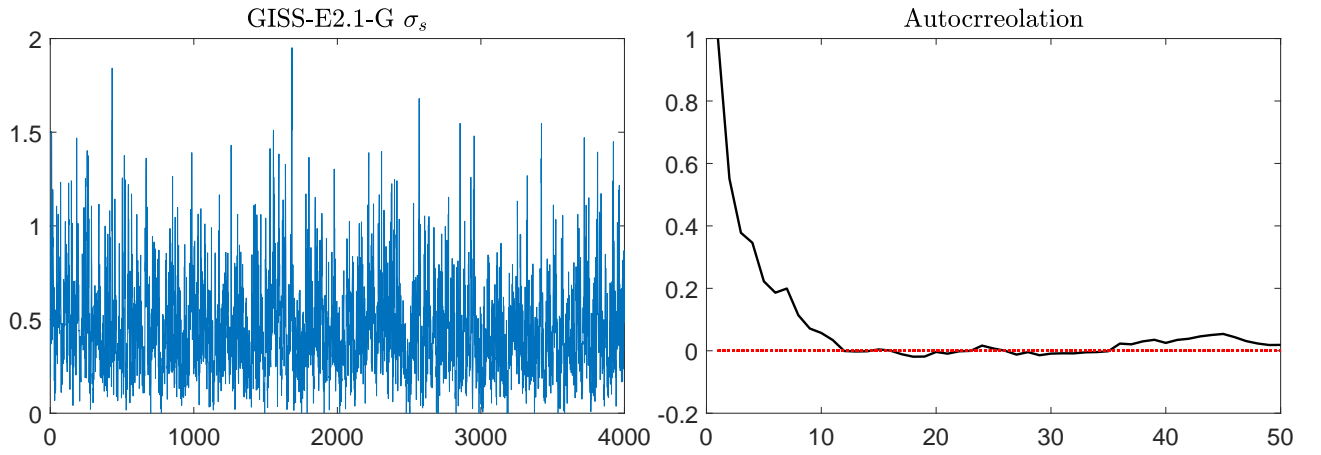


Figure 11: The scaling coefficient of the heat uptake process of ocean surface  $\sigma_s$ . Inefficiency factor: 8.81. Effective sample size: 11.35%.