Bayesian Econometrics for Business & Economics: Assignment 1

By Group 15

Kacper Kaznowski	2803584
Lanlan Hou	2801069
Wa Chak Sou	2796840

School of Business and Economics

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Model with normal distribution and Gibbs sampling

a. With a non-informative prior (flat prior) for μ

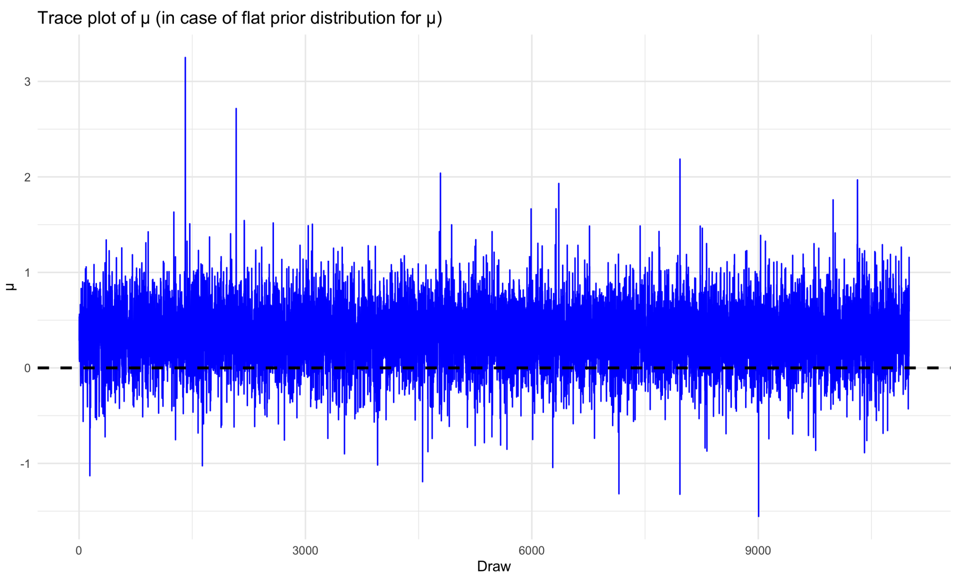

Figure 1.1 Trace plot of μ (in case of flat prior distribution for μ)

Figure 1.1 reveals the trace plot of the simulation of μ using the *Gibbs sampling method* with a **Non-informative prior (flat prior)**. The posterior probabilities are $\Pr(\mu > 0|y) = 0.8796$ and $\Pr(\mu < 0|y) = 0.1205$. There is no strong evidence that the mean is positive. Under a non-informative prior/flat prior, the data provide only weak support for $\mu > 0$.

b. With a normal prior density for μ: $m_{prior} = 0$, $v_{prior} = 10000$

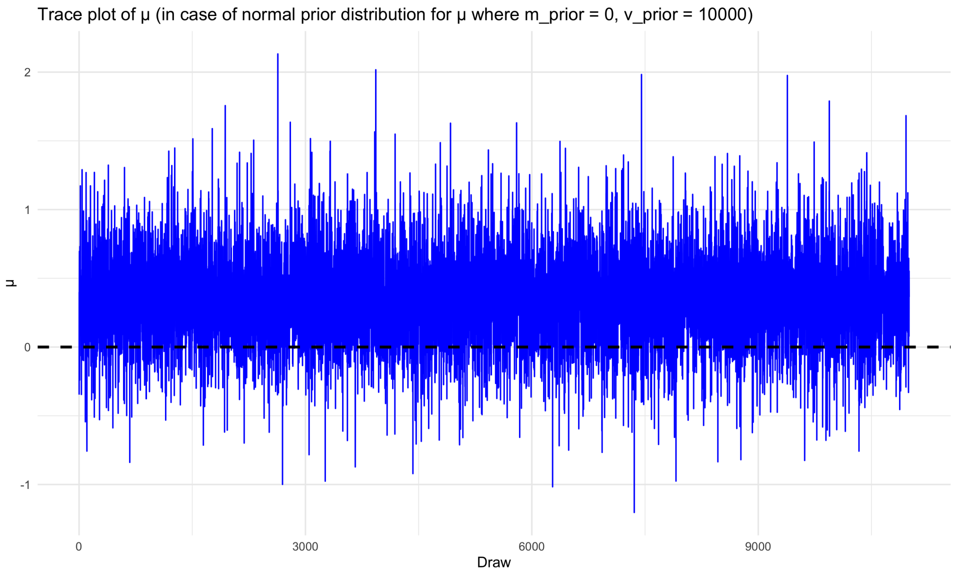

Figure 1.2 Trace plot of μ (in case of normal prior distribution for μ where $m_{prior} = 0$, $v_{prior} = 10000$)

Figure 1.2 reveals the trace plot of the simulation of μ using the *Gibbs sampling method* with a **Normal prior density for** μ**:** $\mu \sim N(0, 100^2)$. The posterior probabilities are $\Pr(\mu > 0|y) = 0.8812$ and $\Pr(\mu < 0|y) = 0.1189$. The Bayesian posterior probabilities are almost identical to part (a). It proves the large prior variance a practically non-informative prior. The posterior is still dominated by the data rather than prior information. The evidence remains statistically weak again.

c. With a normal prior density for μ: $m_{prior} = 0.5$, $v_{prior} = 0.0625$

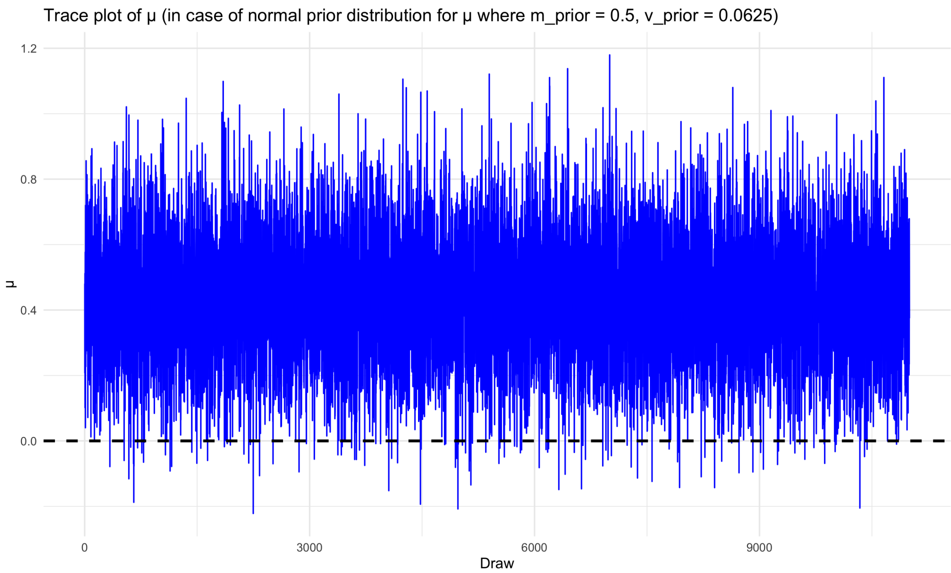

Figure 1.3 Trace plot of μ (in case of normal prior distribution for μ where $m_{prior} = 0.5$, $v_{prior} = 0.0625$)

Figure 1.3 reveals the trace plot of the simulation of μ using the *Gibbs sampling method* with a **Normal prior density for** μ**:** $\mu \sim N(0.5, 0.25^2)$. The posterior probabilities are: $\Pr(\mu > 0|y) = 0.9894$ and $\Pr(\mu < 0|y) = 0.0107$. The result gives a strong evidence that $\mu > 0$. Comparing with the results in part(a) and (b), it illustrates an informative prior can substantially influence posterior inference even in small samples.

d. A classical/frequentist two-sided test

t-Statistic	Degree of Freedom	Acceptance Region (5%)	p-Value	Decision
1.2483	9	[-2.2622, 2.2622]	0.2434	Do not reject H_0

Table 1.4.1: The classical/frequentist two-sided t-test

Part	Prior distribution	$\Pr(\mu > 0 \mid y)$	$\Pr(\mu < 0 \mid y)$
(a)	(Improper) Non-informative prior	0.8796	0.1205
(b)	$\mu \sim N(0, 10000)$	0.8812	0.1189
(c)	$\mu \sim N(0.5, 0.0625)$	0.9894	0.0107

Table 1.4.2: Comparison of results using Bayesian approach with different prior distribution

Table 1.4.1 reveals the result of the classical/frequentist two-sided test. Since the t-test statistic lies within the acceptance region, also with a p-value greater than 0.05, thus do not reject the null H_0 that $\mu = 0$.

Table 1.4.2 summarize the result of the posterior distribution using Bayesian approach under different prior distribution. In contrast to classical/frequentist approach, the Bayesian approach directly quantifies the probability that $\mu > 0$ based on the posterior probabilities between 0.88 (non-informative priors) and 0.99 (informative prior). This result supports that the Bayesian interpretation focuses on probability about parameters given the sample data rather than probability about data under an assumed model in classical/frequentist. It also reflects how prior information can strengthen inference when sample data are limited.