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# Bayesian Econometrics for Business Economics: Assignment 1

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**By Group 15**

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|------------------|---------|
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## Model with normal distribution and Gibbs sampling

### a. With a non-informative prior (flat prior) for $\mu$

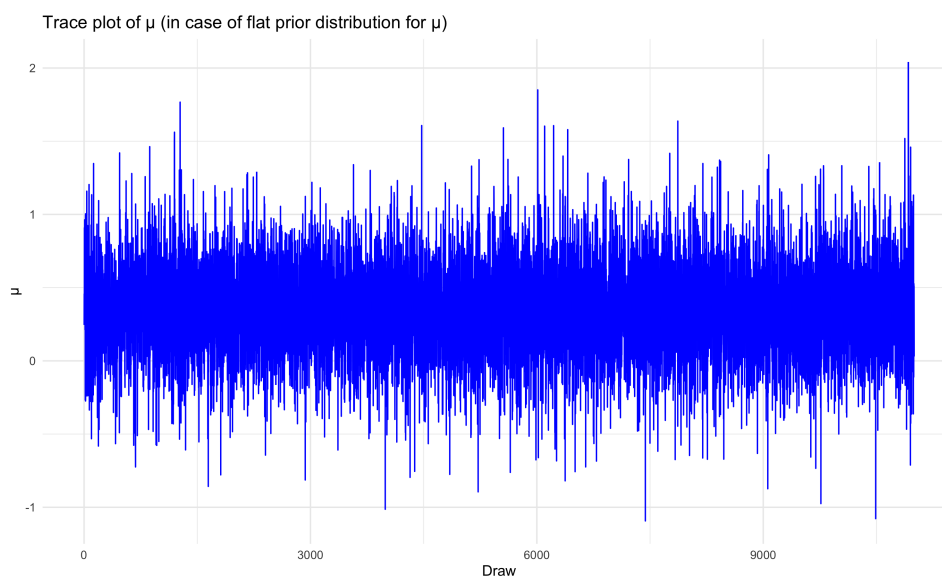


Figure 1.1 Trace plot of  $\mu$  (in case of flat prior distribution for  $\mu$ )

The posterior probabilities are:  $\Pr(\mu > 0|y) = 0.8766$  and  $\Pr(\mu < 0|y) = 0.1235$ .

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

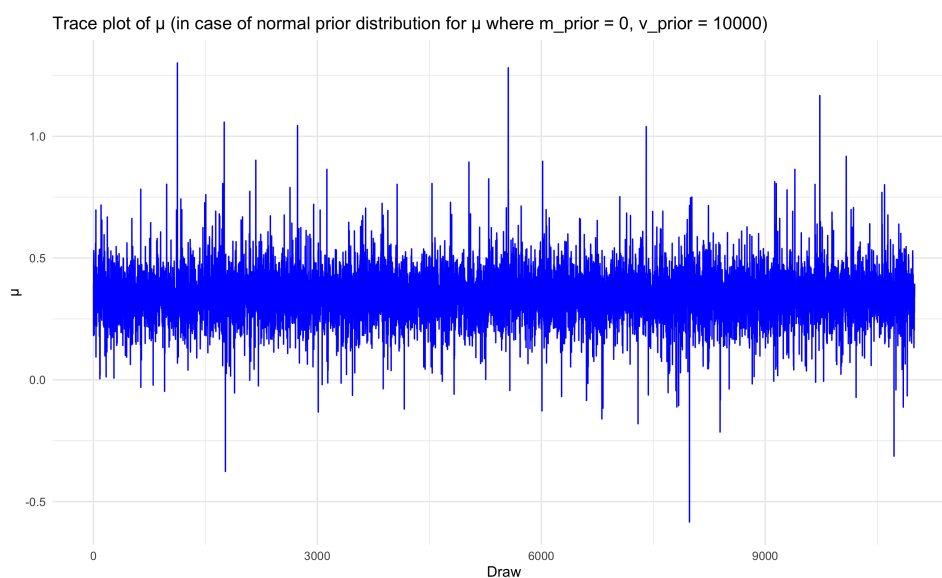


Figure 1.2 Trace plot of  $\mu$  (in case of normal prior distribution for  $\mu$  where  $m_{prior} = 0$ ,  $v_{prior} = 10000$ )

The posterior probabilities are:  $\Pr(\mu > 0|y) = 0.9962$  and  $\Pr(\mu < 0|y) = 0.0039$ .

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

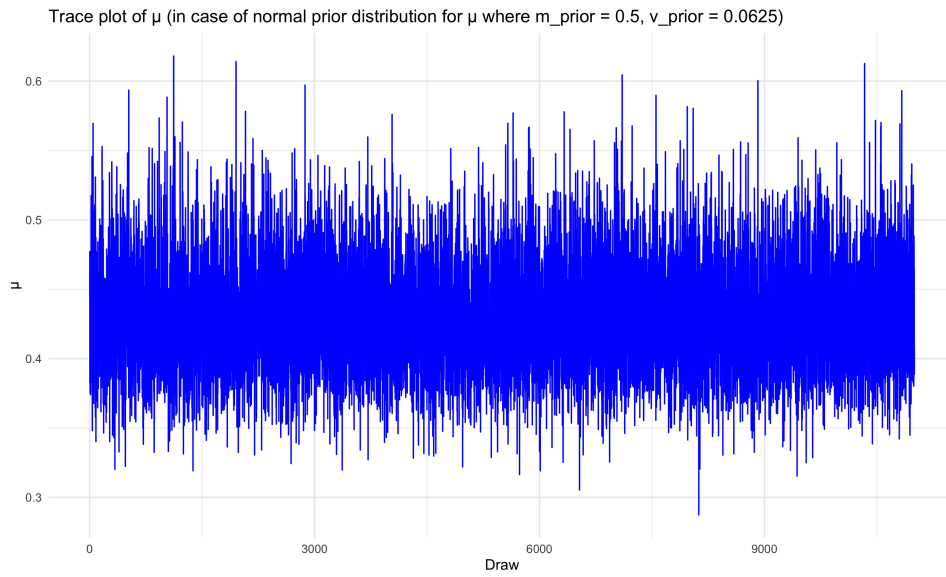


Figure 1.3 Trace plot of  $\mu$  (in case of normal prior distribution for  $\mu$  where  $m_{prior} = 0.5$ ,  $v_{prior} = 0.0625$ )

The posterior probabilities are:  $\Pr(\mu > 0|y) = 1.00$  and  $\Pr(\mu < 0|y) = 0.00$ .

d. A classical/frequentist two-sided test

| Prior Distribution for $\mu$     | Test Statistic | Accept Region       | Decision (5% level) |
|----------------------------------|----------------|---------------------|---------------------|
| (Improper) Non-informative prior | 116.0842       | $[-2.2622, 2.2622]$ | Reject $H_0$        |
| $\mu \sim N(0, 10000)$           | 371.2741       | $[-2.2622, 2.2622]$ | Reject $H_0$        |
| $\mu \sim N(0.5, 0.0625)$        | 1144.5673      | $[-2.2622, 2.2622]$ | Reject $H_0$        |

Table 1.4: Classical two-sided  $t$ -test results for cases (a), (b), and (c)

## Appendix

```

1 library(openxlsx)
2 raw <- read.xlsx('student_groups_stocks.xlsx', sheet = 1)
3
4 groupNumber <- 15
5 nameOfStock <- raw$Stock.Name[groupNumber]
6 startDate <- raw$Start.Date[groupNumber]
7 endDate <- raw$'End.Date.(+10y)'[groupNumber]
8
9 # Compute the start date of the final five years
10 library(lubridate)
11
12 originalDate <- as.Date(startDate)
13 finalFiveYearsStartDate <- originalDate %m+% years(5)
14
15 # Extract the daily stock price from source
16 library(quantmod)
17
18 getSymbols(nameOfStock, src = 'yahoo', from = finalFiveYearsStartDate,
19           to = endDate)
19 date <- index(HSBC)
20
21 # Adjusted Close
22 adjustedPrice <- as.numeric(HSBC[, 'HSBC.Adjusted'])
23
24 # Log Returns
25 compoundedReturns <- numeric(length(adjustedPrice) - 1)
26 for(i in (2:length(adjustedPrice))) {
27   compoundedReturns[i-1] <- log(adjustedPrice[i] / adjustedPrice[i-1])
28 }
29 # Squared Log Returns
30 squaredCompoundedReturns <- compoundedReturns ^ 2
31
32 # Function to compute the ACF and plot the graph
33 plotACF <- function(input_list, input_maxLags, objectName, savePath) {
34   ACFResult <- acf(input_list, lag.max = input_maxLags, plot = FALSE)
35
36   ACFValues <- ACFResult$acf[-1]
37   lags <- ACFResult$lag[-1]
38   numberOfObservations <- length(input_list)
39   confidenceBands <- 1.96 * 1 / sqrt(length(input_list))
40
41   library(ggplot2)
42   plot_df <- data.frame(lag = lags, acf = ACFValues)
43
44   ggplot(plot_df, aes(x = lag, y = acf)) +
45     geom_bar(aes(color = 'ACF'), stat = 'identity',
46             fill = 'blue', width = 0.05) +
47     geom_hline(yintercept = 0, color = 'black') +
48     geom_hline(aes(yintercept = -confidenceBands,
49                   color = '95% Confidence Interval'), linetype = 'dashed')
50     +
51     geom_hline(aes(yintercept = confidenceBands,
52                   color = '95% Confidence Interval'), linetype = 'dashed')
52     +
53     scale_color_manual(name = 'Components',
54                       values = c('ACF' = 'blue',

```

```

54                                     '95% Confidence Interval' = 'red')) +
55     labs(title = paste('ACF for HSBC', objectName, 'for', input_maxLags
56       , 'Lags (2015M11-2020M11)'),
57       x = 'Lag', y = 'ACF') +
58     theme_minimal() +
59     theme(legend.position = c(0.95, 0.95),
60           legend.justification = c("right", "top"),
61           legend.title = element_text(size = 12, face = "bold"),
62           legend.text = element_text(size = 10))
63   ggsave(savePath, width = 10, height = 6, dpi = 300)
64 }
65 returns_result <- plotACF(compoundedReturns,
66   input_maxLags = 50,
67   objectName = 'Log Returns',
68   savePath = 'figures/returns_acf_plot.png')
69
70 squaredReturns_result <- plotACF(squaredCompoundedReturns,
71   input_maxLags = 50,
72   objectName = 'Squared Log Returns',
73   savePath = 'figures/squaredReturns_acf
    _plot.png')

```

Figure 1: Question 1(a)

```

1 # Function to perform the Ljung-Box test and report the result
2 LBTest <- function(input_series, input_maxLags, steps){
3   steppedLags <- seq(steps, input_maxLags, by = steps)
4
5   result_df <- data.frame(Lag = integer(),
6     Statistic = numeric(),
7     Crit_Value = numeric(),
8     P_Value = numeric())
9
10  for (lag in steppedLags) {
11    lb_test <- Box.test(input_series, lag = lag, type = 'Ljung-Box')
12    testStatistic <- as.numeric(lb_test$statistic)
13    pValue <- as.numeric(lb_test$p.value)
14    criticalValue <- qchisq(0.95, df = lag)
15
16    newRow <- data.frame(Lag = lag,
17      Statistic = round(testStatistic, 4),
18      Critical_Value = round(criticalValue, 4),
19      P_Value = signif(pValue, 4))
20
21    result_df <- rbind(result_df, newRow)
22  }
23  return(result_df)
24 }
25
26 returns_LBTest <- LBTest(compoundedReturns, 50, 10)
27 returns_LBTest
28 returns_LBTest <- LBTest(squaredCompoundedReturns, 50, 10)
29 returns_LBTest

```

Figure 2: Question 1(b)

```

1 # compute the MA volatility
2 window <- 300

```

```

3
4 hat_y <- numeric(length(compoundedReturns)-window)
5 MA_volatility <- numeric(length(compoundedReturns)-window)
6
7 for (t in window:length(compoundedReturns)){
8   hat_y[t-window+1] <- mean(compoundedReturns[(t-window+1):(t)])
9   MA_volatility[t-window+1] <- sqrt(1/(window-1) * sum(sapply(0:(window
10     -1),
11                                   function(j) (compoundedReturns[t-j])^2))
12   )
13 }
14
15 # compute the EWMA volatility
16 lambda <- 0.94
17
18 EWMA_volatility <- numeric(length(compoundedReturns)+1)
19
20 for (t in 1:length(compoundedReturns)){
21   EWMA_volatility[t+1] <- sqrt((1 - lambda) * (compoundedReturns[t]^2)
22     + lambda * EWMA_volatility[t]^2)
23 }
24
25 MA_df <- data.frame(MA_vol = MA_volatility,
26   EWMA_vol = EWMA_volatility[window:length(
27     compoundedReturns)],
28   date = date[window:length(compoundedReturns)])
29
30 ggplot(MA_df, aes(x = date)) +
31   geom_line(aes(y = MA_vol, color = 'MA Volatility')) +
32   geom_line(aes(y = EWMA_vol, color = 'EWMA Volatility')) +
33   labs(title = paste('MA Volatility (W=', window,
34     ') and EWMA Volatility ( =', lambda,
35     ') for HSBC Log Returns (2015M11-2020M11)'),
36     x = 'Date', y = 'Volatility', color = 'Model') +
37   theme_minimal()
38 ggsave('figures/ma_plot.png', dpi = 300)

```

Figure 3: Question 2(a)

```

1 # calculate standrized residuals
2 residual <- (compoundedReturns[(window+1):length(compoundedReturns)])
3 residual_MA <- residual / MA_volatility[1:(length(hat_y)-1)]
4 residual_EWMA <- residual / EWMA_volatility[window:(length(
5   compoundedReturns)-1)]
6
7 # residual autocorrelation checking
8 MA_result <- plotACF(residual_MA,
9   input_maxLags = window,
10   objectName = 'Log Returns',
11   savePath = 'figures/residuals_MA_acf_plot.png')
12
13 EWMA_result <- plotACF(residual_EWMA,
14   input_maxLags = window,
15   objectName = 'Squared Log Returns',
16   savePath = 'figures/residuals_EWMA_acf_plot.png',
17   )
18
19 # Distribution of Standardized Residuals
20 residual_df <- data.frame(MA_vol = residual_MA,
21   EWMA_vol = residual_EWMA)

```

```

19
20 ggplot(residual_df, aes(x = MA_vol)) +
21   geom_histogram(aes(y = ..density..),
22                 bins = 50, fill = 'skyblue', color = 'blue') +
23   stat_function(fun = dnorm,
24               args = list(mean = mean(residual_MA, na.rm = TRUE),
25                           sd = sd(residual_MA, na.rm = TRUE)),
26               color = 'black', linewidth = 1, linetype = 'dashed') +
27   labs(title = 'Under MA Volatility Models',
28        x = 'Standardized Residuals', y = 'Density')
29 ggsave('figures/MA_residual_distribution.png', width = 6, height = 6,
30        dpi = 300)
31
32 ggplot(residual_df, aes(x = EWMA_vol)) +
33   geom_histogram(aes(y = ..density..),
34                 bins = 50, fill = 'orange', color = 'darkorange') +
35   stat_function(fun = dnorm,
36               args = list(mean = mean(residual_EWMA, na.rm = TRUE),
37                           sd = sd(residual_EWMA, na.rm = TRUE)),
38               color = 'black', linewidth = 1, linetype = 'dashed') +
39   labs(title = 'Under EWMA Volatility Models',
40        x = 'Standardized Residuals', y = 'Density')
41 ggsave('figures/EWMA_residual_distribution.png', width = 6, height = 6,
42        dpi = 300)
43
44 # Ljung-Box Test
45 MA_LBTest <- LBTest((residual_MA^2), 50, 10)
46 MA_LBTest
47 EWMA_LBTest <- LBTest((residual_EWMA^2), 50, 10)
48 EWMA_LBTest
49
50 library('tseries')
51
52 # Jarque-Bera Test
53 jarque.bera.test(residual_MA)
54 jarque.bera.test(residual_EWMA)

```

Figure 4: Question 2(b)