SGupta_HW02Question3

```r
# Load necessary library
library(faraway)

set.seed(42)  # Set the seed
# Load the dataset
data(uswages)
head(uswages)
```

```
        wage educ exper race smsa ne mw so we pt
6085  771.60   18    18    0    1  1  0  0  0  0
23701 617.28   15    20    0    1  0  0  0  1  0
16208 957.83   16     9    0    1  0  0  1  0  0
2720  617.28   12    24    0    1  1  0  0  0  0
9723  902.18   14    12    0    1  0  1  0  0  0
22239 299.15   12    33    0    1  0  0  0  1  0
```

```r
# Fit the model with weekly wages
model_wage <- lm(wage ~ educ + exper, data = uswages)
# Summary of the model
summary(model_wage)
```

```
Call:
lm(formula = wage ~ educ + exper, data = uswages)

Residuals:
    Min      1Q  Median      3Q     Max
-1018.2  -237.9   -50.9   149.9  7228.6

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept) -242.7994    50.6816  -4.791 1.78e-06 ***
educ          51.1753     3.3419  15.313  < 2e-16 ***
exper          9.7748     0.7506  13.023  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 427.9 on 1997 degrees of freedom
Multiple R-squared:  0.1351,	Adjusted R-squared:  0.1343 
F-statistic:   156 on 2 and 1997 DF,  p-value: < 2.2e-16
```

```r
# Fit the model with logged weekly wages
model_log_weekly_wages <- lm(log(wage) ~ educ + exper, data = uswages)

# Summary of the model
summary(model_log_weekly_wages)
```

```

Call:
lm(formula = log(wage) ~ educ + exper, data = uswages)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.7533 -0.3495  0.1068  0.4381  3.5699 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.650319   0.078354   59.35   <2e-16 ***
educ        0.090506   0.005167   17.52   <2e-16 ***
exper       0.018079   0.001160   15.58   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6615 on 1997 degrees of freedom
Multiple R-squared:  0.1749,	Adjusted R-squared:  0.174 
F-statistic: 211.6 on 2 and 1997 DF,  p-value: < 2.2e-16
```

Model 1: Weekly Wages

The regression equation is: wage = -242.7994 + 51.1753 educ + 9.7748 exper

Intercept (−242.7994): When education and experience are both 0, the predicted weekly wage is −242.80.

Coefficient for educ (51.1753): For each additional year of education, the weekly wage increases by approximately $51.18

Coefficient for exper (9.7748): For each additional year of experience, the weekly wage increases by approximately $9.77

R-squared: 0.1351 (13.51%) of the variation in weekly wages is explained by education and experience.

Model 2: Logged Weekly Wages

The regression equation is: log(wage) = 4.6503 + 0.0905 educ + 0.0181 exper

Intercept (4.6503): When education and experience are 0, the predicted log(wage) is 4.6503.

Coefficient for educ (0.0905): For each additional year of education, the weekly wage increases by approximately 9.05%

Coefficient for exper (0.0181): For each additional year of experience, the weekly wage increases by approximately 1.81%

R-squared: 0.1749 (17.49%) of the variation in logged weekly wages is explained by education and experience.

Model with Weekly Wages provides an absolute change in wages (in dollars) for each additional year of education or experience. Example: An additional year of education increases wages by $51.18.

Model with Logged Weekly Wages provides a percentage change in wages for each additional year of education or experience. Example: An additional year of education increases wages by 9.05%.

The logged weekly wages model provides a more natural interpretation:

It reflects proportional changes in wages, which consider the real-world income growth trends.

It also consider that income is not linear and may exponentially with factors like education.