

# Econometrics Assignment 5

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1.

A)

The coefficient on Midwest loses its statistical significance when moving from model 1 to model 2 because the baseline categorical dummy variable changes from South to West. In each model, Midwest is being compared to the baseline region. While Midwest is significantly different statistically from the South region, it is not significantly different statistically from West. This is also reflected by the proximity of the coefficients for Midwest and West in model 1, 0.0502 and 0.0485, respectively.

B)

Looking at model 1, we see the coefficient for Midwest is 0.0502, meaning that holding all else constant, switching the region from South to Midwest is expected to increase the GPA by 0.0502. The coefficient of 0.100 on Northeast means that holding all else constant in the regression, switching from South to Northeast is expected to result in an increase in GPA of 0.100. To find the average GPA gap between a student in the Midwest and a student in the Northeast, we find the difference between the two coefficients, and see that on average, students in the Northeast have a GPA that is higher than that of their Midwest peers by 0.0498.

C)

The new interpretation of the Northeast coefficient would be the estimated effect on GPA when the region is switched from Midwest to Northeast.

2.

A)

If accidents is a concave function of miles, we would see that in the  $\beta_3$  coefficient of miles squared. In this case, the  $\beta_3$  coefficient would be negative.

B)

To strictly measure the impact of an additional mile driven on accident risk, we would set the change in expected accidents equal to the following:  $\beta_2 + (\beta_3 \times \text{miles})^2 - (\beta_3 \times (\text{miles} - 1))^2$ . In other words, we take the miles coefficient and add the difference of the miles squared coefficient multiplied by number of miles and the miles squared coefficient multiplied by one less than the number of miles. This is necessary to capture the varying impact of number of miles on accident risk given that the function is not linear with respect to miles and therefore does not have a constant slope.

C)

In order to see at what level of miles driven the function reaches its peak, we need to take the derivative of the regression model with respect to miles. The derivative with respect to miles is equal to the following:  $\beta_2 + 2(\beta_3)(\text{miles})$ . Then we set this equal to zero and solve for miles, yielding the peak accident level with respect to miles of negative  $\beta_2$  divided by the quantity 2 times  $\beta_3$ , or  $-\beta_2 / (2 \times \beta_3)$ .

D)

If we re-ran this regression using  $\log(\text{accidents})$  as the Y variable, we would be using a log-linear regression model. Therefore, the interpretation of the coefficient of 0.0078 on alcohol would be that as the driver's total alcohol consumption over the past five years increases by one unit, it is expected that the number of accidents will increase by 0.78%.

3)

A)

Table 1: Data summary

Name	Piped data
Number of rows	4733
Number of columns	15
Column type frequency: numeric	15
Group variables	None

**Variable type: numeric**

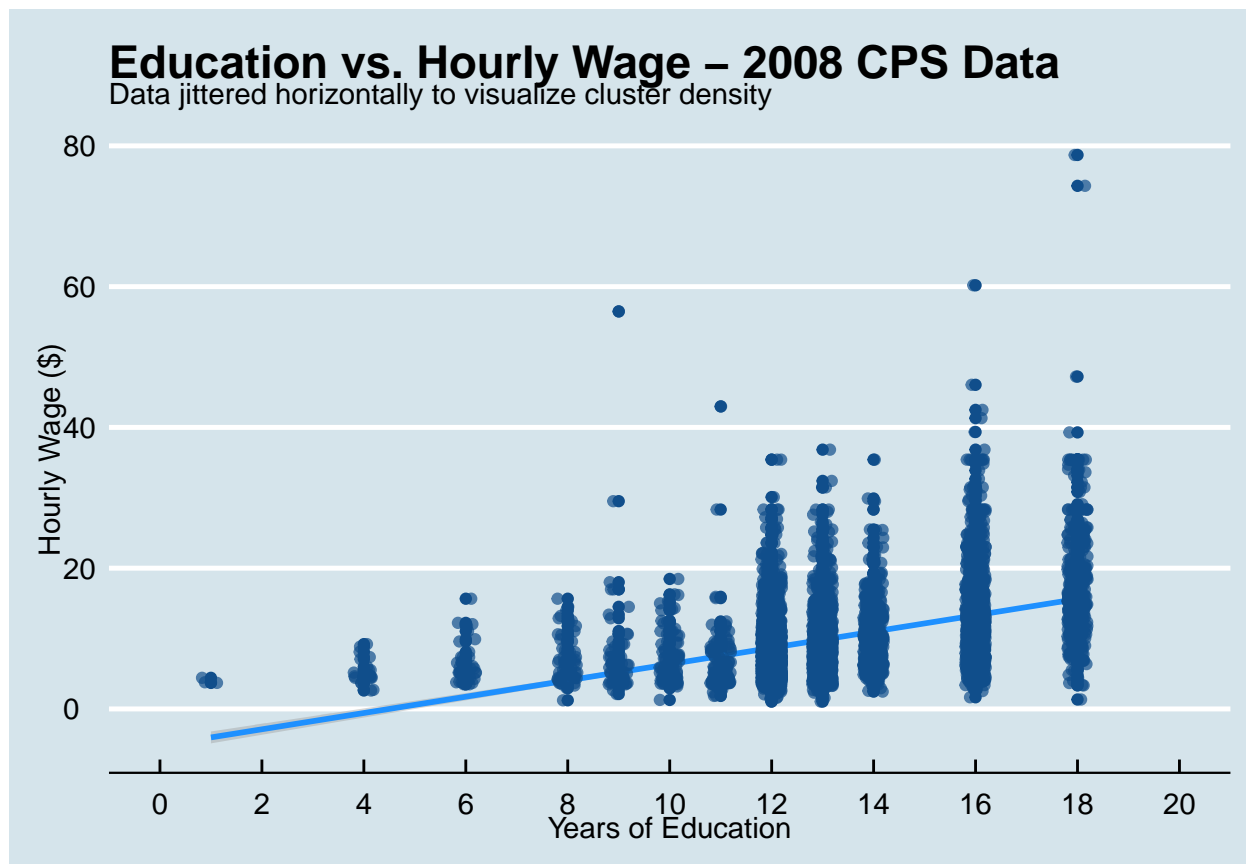
skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
Wage	0	1	10.19	6.21	1.05	5.89	8.53	12.75	78.71
Education	0	1	13.30	2.36	1.00	12.00	13.00	16.00	18.00
Age	0	1	38.33	11.30	18.00	29.00	38.00	47.00	64.00
Experience	0	1	19.04	11.40	0.00	10.00	19.00	27.00	52.00
Female	0	1	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Black	0	1	0.10	0.30	0.00	0.00	0.00	0.00	1.00
White	0	1	0.90	0.30	0.00	1.00	1.00	1.00	1.00
Married	0	1	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Union	0	1	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Northeast	0	1	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Midwest	0	1	0.24	0.43	0.00	0.00	0.00	0.00	1.00
South	0	1	0.31	0.46	0.00	0.00	0.00	1.00	1.00
West	0	1	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Full Time	0	1	0.88	0.32	0.00	1.00	1.00	1.00	1.00
Metropolitan	0	1	0.79	0.40	0.00	1.00	1.00	1.00	1.00

Source: 2008 Current Population Survey

From this summary table of the CPS data, we see that the mean wage is 10.2 dollars per hour with a standard deviation of 6.21 dollars. The median is 8.53 dollars, and the mean is likely pulled to the right of the median due to large salaries including the maximum hourly wage of 78.7 dollars. The average years of education in the data is 13.3 with a standard deviation of 2.36. The average experience is 19 with a fairly wide spread of 11.4 years. 48.5 percent of the observations are from females, 9.87% are black, and 90.1% are white. The most common region is the South, with 31% of the data, followed by Midwest, then West and Northeast.

B)

```
## 'geom_smooth()' using formula 'y ~ x'
```



```

null <- 0
se <- 0.04303063
estimate <- 1.156924

t <- (estimate - null) / se
# Critical t-value at 5% significance level is 1.96.

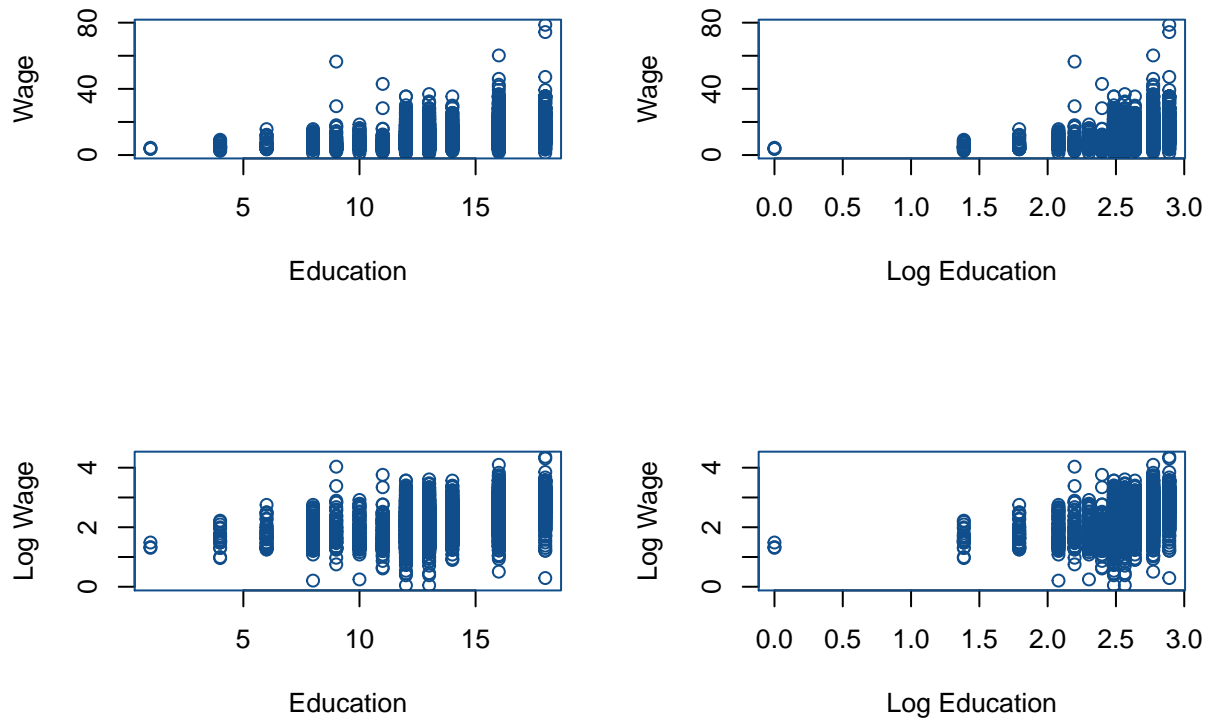
```

When we regress wage on education using the CPS dataset, we find the coefficient on education is approximately 1.16. This means that for an additional year of education, we expect the hourly wage to increase by 1.16 dollars. The robust standard error of the education term is 0.043 and the intercept is -5.20.

Education is statistically significant at the 5% level. We find that the t-value of the education coefficient is approximately 26.89, much larger than the critical value of 1.96. Therefore, we reject the null hypothesis that the education coefficient is equal to zero.

The estimated value of the education coefficient is both statistically significant and practically significant. Each additional year of education is expected to increase hourly wages by 1.16 dollars, which adds up quickly over time, especially given the mean hourly wage of 10.2 dollars.

D)



E)

```
model_1 <- lm(ln_wage ~ ln_educ, data = cps_ln)
model_2 <- lm(ln_wage ~ educ, data = cps_ln)
model_3 <- lm(ln_wage ~ educ + exp, data = cps_ln)
model_4 <- lm(ln_wage ~ educ + exp + female, data = cps_ln)
model_5 <- lm(ln_wage ~ educ + exp + female + female*educ, data = cps_ln)

stargazer(model_1, model_2, model_3, model_4, model_5, type = "text")
```

```
##
## =====
##                                     Dependent variable:
## -----
##                                     ln_wage
##                                     (3)
## (1)                                (2)
## -----
## ln_educ                1.104***
##                        (0.036)
##
## educ                    0.105***
##                        (0.003)
##
## exp                    0.012***
##                        (0.001)
##
```

```

## female
##
##
## educ:female
##
##
## Constant          -0.671***          0.770***          0.426***
##                   (0.093)            (0.041)            (0.043)
## -----
## Observations          4,733          4,733          4,733
## R2                   0.164          0.202          0.263
## Adjusted R2          0.164          0.202          0.263
## Residual Std. Error    0.503 (df = 4731)    0.491 (df = 4731)    0.472 (df = 4730)
## F Statistic          926.475*** (df = 1; 4731) 1,199.766*** (df = 1; 4731) 845.773*** (df = 2; 4730)
## =====
## Note:

```