

# Solutions to Tutorial Questions - Week 4

## Statistics and Econometrics

### Question 1

Consider a model where the return to education depends upon the amount of work experience (and vice versa):

$$\log(wage) = \beta_0 + \beta_1 educ + \beta_2 exper + \beta_3 educ \cdot exper + u$$

1. What is the return to another year of education?
2. State the null hypothesis that the return to education does not depend on the level of *exper*. What do you think is the appropriate alternative?
3. Use the data in `wage2.RData` to test the null hypothesis in part 2 against your stated alternative.
4. Predict the expected wage for an average person with *educ* = 12 and *exper* = 10.

### Solutions

1. Holding *exper* (and the elements in *u*) fixed, we have

$$\Delta \log(wage) = \beta_1 \Delta educ + \beta_3 (\Delta educ) exper = (\beta_1 + \beta_3 exper) \Delta educ,$$

or  $\Delta \log(wage) / \Delta educ = \beta_1 + \beta_3 exper$ , which is the approximate percentage change in *wage* given one more year of education.

2.  $H_0 : \beta_3 = 0$ . If we think that education and experience interact positively – so that people with more experience are more productive when given another year of education – then  $\beta_3 > 0$  is the appropriate alternative.

- 3.

```
load("wage2.RData")
log.wage.model <- lm(log(wage) ~ educ + exper + educ:exper, data)
```

The estimated equation is

$$\widehat{\log(wage)} = 5.95 + .044 educ - .021 exper + .0032 educ \cdot exper,$$

(.24)    (.017)            (.020)            (.0015)

$n = 935$ ,  $R^2 = .135$ ,  $\bar{R}^2 = .132$ . The  $t$  statistic on the interaction term is about 2.095, which gives a  $p$ -value below .02 against  $H_1 : \beta_3 > 0$ . Therefore, we reject  $H_0 : \beta_3 = 0$  against  $H_1 : \beta_3 > 0$  at the 2% level.

- 4.

```
newdata <- data.frame(educ = 12, exper = 10)
predicted.logwage <- predict(log.wage.model, newdata, interval = "none")
predicted.wage <- mean(exp(log.wage.model$residuals)) * exp(predicted.logwage)
predicted.wage
```

```
##          1
## 829.9023
```

The expected wage for an average person with *educ* = 12 and *exper* = 10 is predicted to be around 830.

## Question 2

Use the data from `jtrain.RData` for this exercise.

1. Consider the simple regression model

$$\log(\text{scrap}) = \beta_0 + \beta_1 \text{grant} + u,$$

where *scrap* is the firm scrap rate (percentage of failed assemblies or material that cannot be repaired or restored, and is therefore condemned and discarded), and *grant* is a dummy variable indicating whether a firm received a job training grant. Can you think of some reasons why the unobserved factors in *u* might be correlated with *grant*?

2. Estimate the simple regression model using the data for 1988. (You should have 54 observations) Does receiving a job training grant significantly lower a firm's scrap rate?
3. Now, add as an explanatory variable  $\log(\text{scrap}_{87})$ . How does this change the estimated effect of *grant*? Interpret the coefficient on *grant*. Is it statistically significant at the 5% level against the one-sided alternative  $H_1 : \beta_{\text{grant}} < 0$ ?
4. Test the null hypothesis that the parameter on  $\log(\text{scrap}_{87})$  is one against the two-sided alternative. Report the *p*-value for the test.
5. Repeats parts 3 and 4, using heteroskedasticity-robust standard errors, and briefly discuss any notable differences.

## Solutions

1. If the grants were awarded to firms based on firm or worker characteristics, *grant* could easily be correlated with such factors that affect productivity. In the simple regression model, these are contained in *u*.
- 2.

```
load("jtrain.RData")
data.88 <- data %>% filter(year == 1988) %>% select(lscrap, grant, lscrap_1) %>% na.omit
lscrap.m1 <- lm(lscrap ~ grant, data.88)
```

The simple regression estimates using the 1988 data are

$$\widehat{\log(\text{scrap})} = \underset{(.241)}{.409} + \underset{(.406)}{.057} \text{grant},$$

where  $n = 54$ , and  $R^2 = .0004$ . The coefficient on *grant* is actually positive, but not statistically different from zero.

- 3.

```
lscrap.m2 <- lm(lscrap ~ grant + lscrap_1, data.88)
-qt(0.95, 51)
```

```
## [1] -1.675285
```

When we add  $\log(\text{scrap}_{87})$  to the equation, we obtain

$$\widehat{\log(\text{scrap}_{88})} = \underset{(.089)}{.021} - \underset{(.147)}{.254} \text{grant}_{88} + \underset{(.044)}{.831} \log(\text{scrap}_{87}),$$

where  $n = 54$ ,  $R^2 = .873$ . The *t* statistic for  $H_0 : \beta_{\text{grant}} = 0$  is  $-.254/.147 \approx -1.73$ . The 5% critical value for 51 *df* is around  $-1.68$ . Because  $t = -1.73 < -1.68$ , we reject  $H_0$  in favor of  $H_1 : \beta_{\text{grant}} < 0$  at the 5% level.

- 4.

```
2 * pt(-3.84, 51)
```

```
## [1] 0.0003413515
```

The  $t$  statistic is  $(.831 - 1)/.044 \approx -3.84$  ( $p$ -value  $\approx 0.00034$ ), which is a strong rejection of  $H_0$ .

5.

```
cov <- vcovHC(lscrap.m2, type = "HC1")
robust.se <- sqrt(diag(cov))
stargazer(lscrap.m2, lscrap.m2, se = list(NULL, robust.se), column.labels = c("default", "robust"),
          header = FALSE, type = 'latex', title = "Question 2.5")
```

Table 1: Question 2.5

	<i>Dependent variable:</i>	
	lscrap	
	default (1)	robust (2)
grant	−0.254* (0.147)	−0.254* (0.146)
lscrap_1	0.831*** (0.044)	0.831*** (0.074)
Constant	0.021 (0.089)	0.021 (0.100)
Observations	54	54
R <sup>2</sup>	0.873	0.873
Adjusted R <sup>2</sup>	0.868	0.868
Residual Std. Error (df = 51)	0.513	0.513
F Statistic (df = 2; 51)	174.941***	174.941***
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

```
2 * pt(-2.28, 51)
```

```
[1] 0.026821
```

With the heteroskedasticity-robust standard error, the  $t$  statistic for  $grant_{88}$  is  $-.254/.146 \approx -1.74$ , so the coefficient is slightly more significantly less than zero when we use the heteroskedasticity-robust standard error. The  $t$  statistic for  $H_0 : \beta_{\log(scrap_{87})} = 1$  is  $(.831 - 1)/.074 \approx -2.28$ , which is notably smaller than before. We can reject null at 5% significance level, but not at 1% significance level.