Replication of Examples in Chapter 5

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1 Introduction

This document is to show how to perform hypothesis testing for a single coefficient in a simple linear regression model. I replicate examples that occur in Chapter 5.

2 The OLS estimation

The linear model is

$$TestScore_i = \beta_0 + \beta_1 STR_i + u_i \tag{1}$$

We first read the data, estimate the linear regression model, and get the regression results.

```
library(AER)
library(foreign)
classdata <- read.dta("caschool.dta")

df <- classdata[c("testscr", "str")]
mod1 <- lm(testscr ~ str, data = df)
summary(mod1)

Loading required package: car
Loading required package: lmtest
Loading required package: zoo

Attaching package: 'zoo'</pre>
The following objects are masked from 'package:base':
```

```
as.Date, as.Date.numeric
```

Loading required package: sandwich Loading required package: survival

Call:

lm(formula = testscr ~ str, data = df)

Residuals:

Min 1Q Median 3Q Max -47.727 -14.251 0.483 12.822 48.540

Coefficients:

Residual standard error: 18.58 on 418 degrees of freedom Multiple R-squared: 0.05124, Adjusted R-squared: 0.04897 F-statistic: 22.58 on 1 and 418 DF, p-value: 2.783e-06

summary(mod1) reports the estimated coefficients, their standard errors, t-statistics, and the p-values. It also reports R^2 , SER, and other test statistics that we will learn in the next chapters.

By default, the standard errors reported are computed using the formula of **the homoskedasticity-only standard errors**, which are then used in compute the t-statistics. And the p-values are based on the student-t distribution with 418 degrees of freedom.

3 Hypothesis tests

Now we get into testing the zero hypothesis for β_1 , that is,

$$H_0: \beta_1 = \beta_{1,0} \text{ vs. } H_1: \beta_1 \neq \beta_{1,0}$$

3.1 Get all the quantities used in the test

We use the t-statistic to test such a hypothesis, which has the following formula,

$$t = \frac{\hat{\beta}_1 - \beta_{1,0}}{SE(\hat{\beta}_1)} \tag{2}$$

Upon computing the t-statistic, we compare it with the critical value at the desired significant level, say 5%, which is 1.96 from the standard normal distribution. Also, we can use the t-statistics to get the p-value.

How can we get all the quantities used in this formula? Of course, you can simply copy the values in the output of summary(mod1). But doing so is cumbersome, and very subject to mistakes because of manual operations. More importantly, we cannot have the **heteroskedasticity-robust standard error** of $\hat{\beta}_1$. Fortunately, you can get all the quantities in Equation eq:t-stat-b1 using R functions.

The coefficients

All estimated coefficients can be extracted using the function of coef(), which returns a vector containing all estimated coefficients. By default, the first element in the vector is the estimated intercept. So in our regression, the slope is the second element.

The standard errors.

• The homoskedasticity-only standard errors are reported in the output of summary() by default in R. They can also be extracted with the function, vcov(), which returns a matrix called the covariance matrix, with the diagonal elements representing the variances of the coefficients. Thus, the standard errors are the square roots of the diagonal elements.

```
V <- vcov(mod1)
(se_b1 <- sqrt(V[2, 2]))</pre>
```

[1] 0.4798256

• The heteroskedasticity-robust standard errors are the square roots of the diagonal elements in the **heteroskedasticity-consistent** covariance matrix, obtained using the function of vcovHC() in the sandwich package that is loaded by default. There are several versions of the heteroskedasticity-consistent covariance matrix. What we use is the type of HC1.

```
htV <- vcovHC(mod1, type = "HC1")
(se_b1.rb <- sqrt(htV[2, 2]))
[1] 0.5194892</pre>
```

The t-statistics, the critical value, and the p-value.

The t-statistics using the heteroskedasticity-robust standard errors is then computed by

```
(t_b1.rb <- b1 / se_b1.rb)
str
-4.388557
```

Although we know the critical value at the 5% significant level for a two-sided test is 1.96 with a large sample, we prefer getting the value from a function in R. The critical value at the 5% significance level is in fact the 97.5th percentile of the standard normal distribution, which can be got from the qnorm() function.

```
(c.5 <- qnorm(0.975))
[1] 1.959964
```

The p-value associated with the actual t-statistics is $\Pr(|t| > |t^{act}|) = 2\Phi(-|t^{act}|)$. We can compute the p-value in R, following this definition and using the pnorm() function.

3.2 Use coeftest()

Since hypothesis testing is a very common work in statistics, many R functions have been developed to do it. Here I introduce a function, coeffect(), which is in the package of lmtest, which is loaded through the AER package.

```
coeftest(mod1)
```

t test of coefficients:

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

(Intercept) 698.93295 9.46749 73.8245 < 2.2e-16 ***

str -2.27981 0.47983 -4.7513 2.783e-06 ***

---

Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

By default, it reports the homoskedasticity-only standard errors, the corresponding t-statistics, and the p-values. To get the heteroskedasticity-robust results, we need to add an argument to this function to specify the heteroskedasticity-consistent covariance matrix, which has been defined above as htV <- vcovHC(mod1, type = "HC1").

```
t.tst <- coeftest(mod1, vcov. = htV)
t.b1 <- t.tst["str", "t value"]
-4.38855724131497</pre>
```

3.3 TODO Confidence interval

Finally, we can construct the 95% confidence interval of β_1 using the function of confint().

TODO Replace confidence interval with the heteroskedasticity-robust SE

Since there is no existing function to report the confidence interval with heteroskedasticity-robust SE, we can write a user-defined function to do that.

```
conf_interval_robust <- function(lm_obj, param, vcov_ = vcov(lm_obj),</pre>
 level = 0.05){}
    ## This function generates a two-sided confidence interval for a
    ## parameter in the linear regression model with a specified
    ## covariance matrix. The inputs The output
    ## get all the parameters' names and select one based on param
    all_param <- attr(lm_obj$coefficients, "names")</pre>
    which_param <- grep(param, all_param)</pre>
    ## get the estimated parameter and its standard error
    bhat_param <- coef(lm_obj)[which_param]</pre>
    sd_param <- sqrt(vcov_[which_param, which_param])</pre>
    ## get the critical value
    cv <- qnorm(1 - level/2)</pre>
    ## calculate the confidence interval
    lower <- bhat_param - cv * sd_param</pre>
    upper <- bhat_param + cv * sd_param</pre>
    conf_interval <- c(lower, upper)</pre>
    names(conf_interval) <- c("lower", "upper")</pre>
    return(conf_interval)
}
```

4 TODO Dummy variable

A dummy variable can be represented using a factor object in R. There are many ways to create a dummy variable. Here I will create a dummy variable

$$D_i = \begin{cases} 1, & \text{if } str < 20\\ 0, & \text{if } str \ge 20 \end{cases}$$

The R command to create such a dummy variable is as follows

```
D <- factor(ifelse(df$str < 20, 1, 0))
```

The function ifelse() creates a vector consisting of 1 and 0. The first argument in this function is a condition, df\$str < 20. If the condition is satisfied for an element in df\$str, the corresponding element in D is 1, otherwise 0. The function factor() converts the numeric vector to a factor vector.

4.1 TODO Add a scatterplot with the dummy variable

Then we can estimate the linear regression of test scores against the dummy variable, and do the zero hypothesis test.