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9. Dummy Variable Regression Models

In the previous chapter, the dependent and independent variables in our multiple regression models have had **quantitative** meaning. For example, the salary of CEO,annual firm sales,return on equity in percent, and return on firm's stock. In each case the magnitude of the variable conveys useful information.

However, in the empirical work, we must also incorporate **qualitative factors** into regression models. The gender or race of an individual, the industry of a firm (manufacturing, retail, and so on), and the region in Thailand where a city is located (north, south, west, and so on) are all considered as the qualitative factors.

9.1 Describing Qualitative Information

Normally, qualitative factors often come in the form of binary information:

> **Example:**
>
> [1] A person is female or male or female.
>
> [2] A firm offers a certain kind of employee pension plan or it does not.
>
> [3] A farm is located nearby the dam or not.
>
> All of these examples, the relevant information can be captured by defining a **binary variable** or a zero-one variable.
>
> In econometrics, binary variables are most commonly called **dummy variables**, although this name is not especially descriptive.

DUM$_1$ = 0 if ♀
DUM$_1$ = 1 if ♂

DUM$_2$ = 0 if single
DUM$_2$ = 1 if married.

SALARY YEARS EDUCATION GENDER MARITIAL STATUS

FIRM i | y | x_2 | x_3 | DUM$_1$ | DUM$_2$
1
2
3
4
5

In defining a dummy variable, we must decide which event is assigned the value one and which is assigned the value zero.

Question: Why do we use the the values zero and one to describe qualitative information?

Answer: These values are arbitrary: any two different values would do. The real benefit of capturing qualitative information using zero-one variable is that it leads to regression models where the parameters have very natural interpretations.

9.1.1 A Single Dummy Independent Variable

Suppose we would like to estimate the following simple model of hourly wage determination:

$$wage_i = \beta_0 + \delta_0 \text{female} + \beta_1 \text{edu} + u_i \quad (n = 526 \text{ employees})$$

FEMALE = 1 if the person is female
FEMALE = 0 if the person is male

FOR FEMALE : $wage_i = \beta_0 + \delta_0(1) + \beta_1 edu + u_i$

FOR MALE : $wage_i = \beta_0 + 0 + \beta_1 edu + u_i$

δ_0 measures/reflects "WAGE DIFFERENTIAL" BET. MALES AND FEMALES, given the same level of education.

If $\delta_0 < 0$, it means that on average, females earn less than males, given the same level of education.

$$E(wage \mid female = 1, edu) = \beta_0 + \delta_0 \cdot 1 + \beta_1 edu$$
$$= (\beta_0 + \delta_0) + \beta_1 \cdot edu \quad \text{— ①}$$

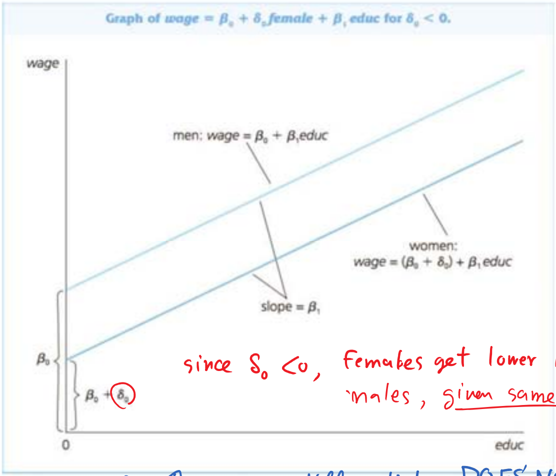
$$E(wage \mid \underbrace{female = 0}_{(=male)}, edu) = \beta_0 + \delta_0 \cdot 0 + \beta_1 \cdot edu$$
$$= \beta_0 + \beta_1 \cdot edu \quad \text{— ②}$$

① − ②; $E(wage \mid female = 1, edu) - E(wage \mid \underbrace{female = 0}_{(\Rightarrow male)}, edu)$

$= \delta_0$.

Gender Effect on wage differential!

Figure 9.1: Graph of Wage



since $\delta_0 < 0$, Females get lower wage compare to males, given same edu level.

NOTE: The wage differential DOES NOT depend on level of education,
That's why the wage-education profiles of the two are "PARARELL."

$$wage = \beta_0 + \delta_0 \cdot FEMALE + \beta_1 \cdot EDU + u_i$$

FEMALE = 1 if female
FEMALE = 0 if male. (male as a base group)

The group we assign "0" is called "Benchmark group" OR "Base Group"
(= the group that you make a comparison against it)

$\boxed{\begin{array}{l} FEMALE = 0 \text{ if female} \\ FEMALE = 1 \text{ if male} \end{array}}$ (Female as base group)

OR

$\boxed{\begin{array}{l} MALE = 1 \text{ if male} \\ MALE = 0 \text{ if female} \end{array}}$ (female as base group)

Ex: $wage = \alpha_0 + \gamma_0 MALE + \beta_1 EDU + u_i$

$\boxed{\begin{array}{l} MALE = 1 \text{ if male} \\ MALE = 0 \text{ if female} \end{array}}$ (Female is base group)

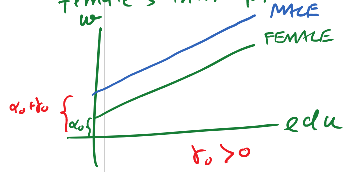
male interept

$E(wage \mid MALE = 1, EDU) = \alpha_0 + \gamma_0 + \beta_1 EDU$ — ①

$E(wage \mid male = 0, EDU) = \alpha_0 + \beta_1 EDU$ — ②

① − ② : $E(wage \mid MALE = 1, EDU) - E(wage \mid MALE = 0, EDU) = \gamma_0$.

female's intercept



$\gamma_0 > 0$

Now, we added more variables into the wage model. Taking males as the base group, a model that controls for experience and tenure in addition to education is

$$wage_i = \beta_0 + \delta_0 female + \beta_1 edu + \beta_2 exper + \beta_3 tenure + u_i$$

female = 1 if female
female = 0 if male
so, male is the base group

If edu, expert, and tenure are all relevant productivity characteristics, the null hypothesis of no difference between men and women (No wage discrimination) is:

$H_0: \delta_0 = 0$ (No wage discrimination)
$H_1: \delta_0 < 0$ (wage discrimination)

In table 9.1, it represents the partial listing of the sample data of wage model. We see that Person 1 is female, Person 2 is female , Person 3 is male, and so on.

Table 9.1: A Partial Listing of the Wage Data.

Data Editor (Browse) - [WAGE1]
File Edit View Data Tools
wage[1] 3.0999999

	wage	educ	exper	tenure	female
1	3.1	11	2	0	1
2	3.2	12	22	2	1
3	3	11	2	0	0
4	6	8	44	28	0
5	5.3	12	7	2	0
6	8.8	16	9	8	0
7	11	18	15	7	0
8	5	12	5	3	1
9	3.6	12	26	4	1
10	18	17	22	21	0
11	6.3	16	8	2	1
12	8.1	13	3	0	1
13	8.8	12	15	0	0

4	6	8	44	28	0
5	5.3	12	7	2	0
6	8.8	16	9	8	0
7	11	18	15	7	0
8	5	12	5	3	1
9	3.6	12	26	4	1
10	18	17	22	21	0
11	6.3	16	8	2	1
12	8.1	13	3	0	1
13	8.8	12	15	0	0
14	5.5	12	18	3	0
15	22	12	31	15	0
16	17	16	14	0	0
17	7.5	12	10	0	1
18	11	13	16	10	1
19	3.6	12	13	0	1
20	4.5	12	36	6	1
21	6.9	12	11	4	1
22	8.5	12	29	13	0
23	6.3	16	9	9	1
24	.53	12	3	1	1
25	6	11	37	8	1
26	9.6	16	3	3	0
27	7.8	16	11	10	0
28	13	16	31	0	0
29	13	15	30	0	0
30	3.3	8	9	1	1
31	13	14	23	5	0
32	4.5	14	2	5	1
33	9.7	13	16	16	1

Table 9.2: The command function to estimate the wage model in STATA program

Table 9.3: $wage_i = \beta_0 + \delta_0 \textbf{female} + \beta_1 \textbf{edu} + \beta_2 \textbf{exper} + \beta_3 \textbf{tenure} + u_i$

```
. reg wage female educ exper tenure
```

Source	SS	df	MS
Model	2603.10658	4	650.776644
Residual	4557.30771	521	8.7472317
Total	7160.41429	525	13.6388844

Number of obs	=	526
F(4, 521)	=	74.40
Prob > F	=	0.0000
R-squared	=	0.3635
Adj R-squared	=	0.3587
Root MSE	=	2.9576

wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
female	-1.810852	.2648252	-6.84	0.000	-2.331109	-1.290596
educ	.5715048	.0493373	11.58	0.000	.4745802	.6684293
exper	.0253959	.0115694	2.20	0.029	.0026674	.0481243
tenure	.1410051	.0211617	6.66	0.000	.0994323	.1825778
_cons	-1.567939	.7245511	-2.16	0.031	-2.991339	-.144538

Example: the Hourly Wage Equation:

$$\begin{aligned} \widehat{\text{wage}} &= -1.5679 - 1.8109\,\text{female} + 0.5715\ \text{edu} + 0.025\ \text{exper} + 0.141\ \text{tenure} \\ &= (0.7246) \quad (0.2648) \qquad (0.0493) \qquad (0.0116) \qquad (0.0212) \end{aligned} \tag{9.1}$$

$R^2 = 0.3635 \quad n = 526$

Interpret the model:

The intercept: The intercept for men is negative. This negative intercept is not so informative since no employee in the sample has zero value of wage for all of edu, exper, tenure.

The Coefficient for female = −1.8109.

If we take a woman and a man with the same levels of education, experience, and tenure, the woman earns, on average, 1.81 $/hr less than the man!

The wage differential of 1.81 $ comes from .... gender or factors associated w/ gender that we have not controlled for the regression

Table 9.4: $wage_i = \beta_0 + \delta_0 \textbf{female} + u_i$

```
reg wage female
```

Source	SS	df	MS
Model	828.220467	1	828.220467
Residual	6332.19382	524	12.0843394
Total	7160.41429	525	13.6388844

Number of obs	=	526
F(1, 524)	=	68.54
Prob > F	=	0.0000
R-squared	=	0.1157
Adj R-squared	=	0.1140
Root MSE	=	3.4763

wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
female	-2.51183	.3034092	-8.28	0.000	-3.107878	-1.915782
_cons	7.099489	.2100082	33.81	0.000	6.686928	7.51205

$\hat{\text{wage}} = \underset{\beta_0}{7.10} - \underset{\delta_0}{2.51}\ \text{FEMALE}$

E(wage | female = 0) = 7.10 $/hr

E(wage | female = 1) = 7.10 − 2.51(1) = 4.59 $/hr.

The coefficient on female

The estimated difference is −2.51

Notice that the model w/ edu, exper, tenure gives

The coefficient on female $7.10 - 2.51(1) = 4.59$ \$/hr.

The estimated difference is -2.51

Notice that the model w/ edu, exper, tenure gives lower value of wage differential (-1.81) — why?

It is informative to compare the coefficient on female in the above equation to the estimate we get when all other explanatory variables are dropped from the equation:

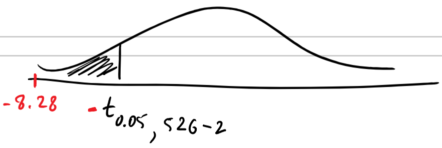
$$\boxed{\begin{aligned}\widehat{\text{wage}} &= 7.0995 - 2.5118\ \text{female} \\ se &= (0.2100) \qquad (0.3034)\end{aligned}} \tag{9.2}$$

$R^2 = 0.1157 \quad n = 526$

$H_0: \delta_0 = 0$

$H_1: \delta < 0 \qquad (\alpha = 0.05)$

$t = \dfrac{-2.50}{0.30} = -8.28$



9.2 Interpreting Coefficients on Dummy Explanatory Variables When the Dependent Variable is log(y)

In this section, we will study a model that has the dependent variable appearing in logarithmic form, with one or more dummy variables approving as independent variables.
Question: How do we interpret the dummy variable coefficients in this case?

Answer: Not surprisingly, the coefficients have a percentage interpretation.

Let us reestimate the wage equation , using log (wage) as the dependent variable and adding quadratics in expert and tenure:

$$log(wage_i) = \beta_0 + \delta_0 female + \beta_1 edu + \beta_2 exper + \beta_3 exper^2 + \beta_4 tenure + \beta_5 tenure^2 + u_i$$

The Stata result is shown in table 9.5.

Table 9.5:

```
reg lwage female educ exper expersq tenure tenursq
```

Source	SS	df	MS
Model	65.3791009	6	10.8965168
Residual	82.9506505	519	.159827843
Total	148.329751	525	.28253286

Number of obs	= 526
F(6, 519)	= 68.18
Prob > F	= 0.0000
R-squared	= 0.4408
Adj R-squared	= 0.4343
Root MSE	= .39978

lwage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
female	-.296511	.0358055	-8.28	0.000	-.3668524	-.2261696
educ	.0801967	.0067573	11.87	0.000	.0669217	.0934716
exper	.0294324	.0049752	5.92	0.000	.0196585	.0392063
expersq	-.0005827	.0001073	-5.43	0.000	-.0007935	-.0003719
tenure	.0317139	.0068452	4.63	0.000	.0182663	.0451616
tenursq	-.0005852	.0002347	-2.49	0.013	-.0010463	-.0001241
_cons	.416691	.0989279	4.21	0.000	.2223425	.6110394

Example: Log Hourly Wage Equation:

$\hat{\delta}_0$

$$\widehat{\log(wage)} = \underset{(0.0989)}{0.4167} - \underset{(0.0358)}{0.2965}\ female + \underset{(0.0068)}{0.0802}\ edu + \underset{(0.0050)}{0.0294}\ exper - \underset{(0.0001)}{0.0006}\ exper^2 + \underset{(0.0068)}{0.0317}\ tenure - \underset{(0.0002)}{0.0006}\ tenure^2 \quad (9.3)$$

$R^2 = 0.4408 \quad n = 526$

Interpret the model:

The coefficient on female : -0.2965

For the same level of education, experience, and tenure, female earns $100 \cdot (0.2965) = 29.7\%$ less than male.

Recall this

$\ln y = \beta_0 + \beta_1 X$

$\frac{d \ln y}{dx} = \beta_1$

$\frac{1}{y}\frac{dy}{dx} = \beta_1$

$\frac{\frac{dy}{y} \times 100}{dx} = \beta_1 \times 100$

$\frac{\% \Delta y}{\Delta x} = \beta_1 \cdot 100$

However, this method is an approximation.

We can have a precise calculation by computing the exact percentage difference in predicted wages:

We know that, holding other factors constant,

$$\widehat{\log(wage_F)} - \widehat{\log(wage_M)} = -0.2965$$

$$\log\left(\widehat{\frac{wage_F}{wage_M}}\right) = -0.2965$$

$$\underbrace{\exp(-0.2965) - 1}_{\approx -0.257\ ***} = \frac{\widehat{wage_F} - \widehat{wage_M}}{\widehat{wage_M}}$$

More accurate estimate says that female's wage is, on average, 25.7% below "A comparable male's wage.

$\underbrace{\text{female } ♀ \quad \text{V.s} \quad \text{male } ♂}_{\text{same educ, exper, tenure}}$

9.3 Using Dummy Variables for Multiple Categories

We can use several dummy independent variables in the same equation. For example, we could add the dummy variable **married** to the wage model.

The previous model:

$$log(wage_i) = \beta_0 + \delta_0 female + \beta_1 edu + \beta_2 exper + \beta_3 exper^2 + \beta_4 tenure + \beta_5 tenure^2 + u_i$$

Now, Let us estimate a model that allows for wage differences among four groups:

[1.] Married Men

[2] Married Women

[2] Married Women

[3] Single Men

[4] Single Women

To do this, we must select a base group:

Let's use " single men " as our base group

our base group

		MARRIED 0	MARRIED 1
FEMALE	0	SINGLE MEN (0,0)	MARRIED MEN (0,1)
	1	SINGLE WOMEN (1,0)	MARRIED WOMEN (1,1)

NOTE (GENDER , MARITIAL STATUS)

Now, we need to define dummy variables for each of the remaining groups.

FEMALE, MARRIED

(0, 1) → Married Men → MARRMALE

(1,0) → Single Women → SINGFEM

(1, 1) → Married Women → MARRFEM

Therefore, our model is:

$$\log(wage_i) = \beta_0 + \delta_0 \underline{marrmale} + \delta_1 \underline{marrfem} + + \delta_2 \underline{singfem} +$$
$$\beta_1 edu + \beta_2 exper + \beta_3 exper^2 + \beta_4 tenure + \beta_5 tenure^2 + u_i$$

MARRMALE	MARRFEM	SINGFEM		SINGMALE
0	0	0	→ SINGLE MALE	1
1	0	0	→ MALE	0
0	0	1	→ SINGLE FEMALE	0
0	1	0	→ MARRIED FEMALE	0

Define m = # of catagories (here $m = 4$)

the maximum number of dummy variables we can put into the model = $m - 1$ variables

We of course drop the dummy variable (female). (Why?)

* WARNING *

Here , if we add " single men " into the regression model , we will face w/ " Perfect collinearity and then the model cannot be solved .

(" DUMMY VARIABLE TRAP "

Table 9.5:

```
reg lwage marrmale marrfem singfem educ exper expersq tenure tenursq
```

Source	SS	df	MS		
Model	68.3617623	8	8.54522029	Number of obs =	526
Residual	79.9679891	517	.154676961	F(8, 517) =	55.25
				Prob > F =	0.0000
				R-squared =	0.4609
				Adj R-squared =	0.4525
Total	148.329751	525	.28253286	Root MSE =	.39329

log(wage)

lwage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
marrmale	.2126757	.0553572	3.84	0.000	.103923	.3214284
marrfem	-.1982676	.0578355	-3.43	0.001	-.311889	-.0846462
singfem	-.1103502	.0557421	-1.98	0.048	-.219859	-.0008414
educ	.0789103	.0066945	11.79	0.000	.0657585	.092062
exper	.0268006	.0052428	5.11	0.000	.0165007	.0371005
expersq	-.0005352	.0001104	-4.85	0.000	-.0007522	-.0003183
tenure	.0290875	.006762	4.30	0.000	.0158031	.0423719
tenursq	-.0005331	.0002312	-2.31	0.022	-.0009874	-.0000789
_cons	.3213781	.100009	3.21	0.001	.1249041	.5178521

$$\widehat{\log(wage)} = \underset{(0.1000)}{0.3214} + \underset{(0.0554)}{0.2127}\ \text{marrmale} - \underset{(0.0578)}{0.1983}\ \text{marrfem} - \underset{(0.0557)}{0.1104}\ singfem$$
$$+ \underset{(0.0067)}{0.0789}\ edu + \underset{(0.0268)}{0.0268}\ exper - \underset{(0.0001)}{0.0005}\ exper^2 + \underset{(0.0068)}{0.0291}\ tenure - \underset{(0.0002)}{0.0005}\ tenure^2$$

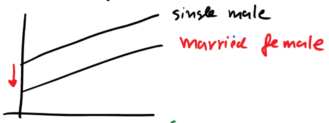
$$\widehat{\log(\text{wage})} = \underset{(0.1000)}{0.3214} + \underset{(0.0554)}{0.2127}\ \text{marrmale} - \underset{(0.0578)}{0.1983}\ \text{marrfem} - \underset{(0.0557)}{0.1104}\ singfem$$
$$+\underset{(0.0067)}{0.0789}\ edu + \underset{(0.0268)}{0.0268}\ exper - \underset{(0.0001)}{0.0005}\ exper^2 + \underset{(0.0068)}{0.0291}\ tenure - \underset{(0.0002)}{0.0005}\ tenure^2 \quad (9.4)$$

$R^2 = 0.4609 \quad n = 526$

RECALL THAT "SINGLE MEN" IS OUR BASE GROUP

-0.1983 marrfem — $(0,1,0)$ vs. single male $(0,0,0)$

On average, married female workers earn $100 \cdot (0.1983) = 19.83\%$ "LOWER" compared to single male workers (our base group), given the same qualifications (i.e., same edu, same exper, same tenure.



$+0.2127$ marrmale — $(1,0,0)$

w/ the same qualifications, ~~same~~ married male are expected to earn 21.27% HIGHER THAN single men (= base group)

$-0.1104 \cdot$ singfem — $(0,0,1)$

w/ the same qualifications, single female earn 11.04% LOWER THAN single men group.

Q: How about wage differential between "SINGLE FEMALE AND "MARRIED FEMALE"?

♀ + married : -0.1983

♀ + SINGLE : -0.1104

① SINGLE MEN

② SINGLE WOMEN

MARRIED WOMEN

Interpret the model: $\Delta W = 0.1983 - 0.1104 = 0.0879$

0.1983 → ♀ + married; 0.1104 → ♀ + SINGLE

Single women earn about $0.0879 \times 100 = 8.8\%$ More than Married women, on average.

9.3.1 Interactions Involving Dummy Variables

8.5.1 The Interactions Among Dummy Variables:

We can recast the model by adding an **interaction term** between female and married to the model where female and married appear separately. This allows the marriage premium to depend on gender. The estimated model with the female-married interaction term is :

$$
\begin{aligned}
\widehat{\log(wage)} &= \underset{(0.100)}{0.321} - \underset{(0.056)}{0.110}\ female + \underset{(0.055)}{0.213}\ married \\
&\quad + \underset{(0.072)}{0.301}\ female \cdot married + \ldots,
\end{aligned} \tag{9.5}
$$

let's consider Married Women :

Intercept $= 0.321 - 0.110(1) + 0.213(1) + 0.301(1 \cdot 1)$

$= +0.725$

- Intercept for single men $= 0.321$
- Intercept for single women $= 0.321 - 0.110(1) + 0.213(0) + 0.301(1 \cdot 0)$

  $= 0.321 - 0.110$

  $= 0.211$
- Intercept for married men $= 0.321 + 0.213(1)$

  $=$

8.5.2 The interaction between Dummy Variable/s and Explanatory Variable/s: the Allowing for the Different Slopes

There are also occasions for interacting dummy variables with explanatory variables that are not dummy variables to allow for a **difference in slope.**

To see the interaction between female and edu, we can rewrite the model as follow:

$$wage_i = (\beta_0 + \delta_0 \underline{\text{female}}) + (\beta_1 \underline{\text{edu}} + \delta_1 \underline{female \cdot edu}) + u_i$$

Women
Group we plug female =1

Therefore: $\boxed{wage = (\beta_0 + \delta_0) + (\underline{\underline{\beta_1 + \delta_1}})\, edu + u}$

Return on Education

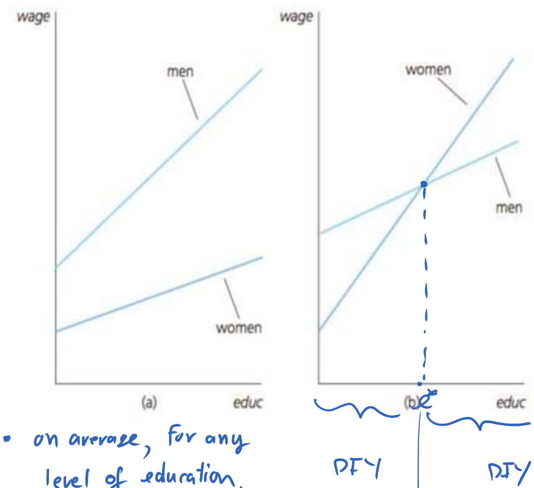
- δ_0 captures the difference in "intercept" between Men and Women
- δ_1 captures the difference in "slope" between Men and Women.

Men
Group we plug female =0

Therefore: $\boxed{wage = \beta_0 + \beta_1 edu + u}$

Figure 9.2: Graph of the Wage Model with an Interaction between female and education

Graphs of equation (7.16): (a) $\delta_0 < 0$, $\delta_1 < 0$; (b) $\delta_0 < 0$, $\delta_1 > 0$.



- on average, for any level of education, Women earn less than Men.
- The higher the education level, the larger the wage gap between Women and Men

Example

Table 9.5:

```
gen femed = female*educ

reg lwage female educ femed exper expersq tenure tenursq
```

Source	SS	df	MS
Model	65.4081534	7	9.34402192
Residual	82.921598	518	.160080305
Total	148.329751	525	.28253286

Number of obs	= 526
F(7, 518)	= 58.37
Prob > F	= 0.0000
R-squared	= 0.4410
Adj R-squared	= 0.4334
Root MSE	= .4001

lwage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
female	-.2267886	.1675394	-1.35	0.176	-.5559289	.1023517
educ	.0823692	.0084699	9.72	0.000	.0657296	.0990088
femed	-.0055645	.0130618	-0.43	0.670	-.0312252	.0200962
exper	.0293366	.0049842	5.89	0.000	.019545	.0391283
expersq	-.0005804	.0001075	-5.40	0.000	-.0007916	-.0003691
tenure	.0318967	.006864	4.65	0.000	.018412	.0453814
tenursq	-.00059	.0002352	-2.51	0.012	-.001052	-.000128
_cons	.388806	.1186871	3.28	0.001	.1556388	.6219732

δ_1

$$\begin{aligned}\widehat{\log(wage)} = &\ 0.3889 - 0.2268\ female + 0.082\ edu - 0.0056\ female\cdot edu \\ &(0.1187) \quad (0.1675) \quad (0.0085) \quad (0.0131) \\ &+ 0.0293\ exper - 0.0006\ exper^2 + 0.0319\ tenure - 0.00059\ tenure^2 \\ &(0.0050) \quad (0.0001) \quad (0.0069) + \quad (0.0002)\end{aligned} \tag{9.6}$$

$R^2 = 0.4410 \quad n = 526$

FOR MALE GROUP (FEMALE = 0)

$\log(wage) = 0.3889 + 0.082\ edu + \ldots$

FOR FEMALE GROUP (FEMALE = 1)

$\log(wage) = (\underset{\hat\beta_0}{0.3889} \underset{\hat\delta_0}{-0.2268}) + (\underset{\hat\beta_1}{0.082} \underset{\hat\delta_1}{-0.0056})\,edu + \ldots$

→ Estimated ROE for Men = $0.082 \times 100 = 8.2\%$

%Δ in wage

→ Estimated ROE for Women = $(0.082 - 0.0056) \times 100$

$= 0.0764 \times 100 = 7.64\%$

$\boxed{\begin{aligned} H_0 &: \delta_1 = 0 \\ H_1 &: \delta_1 \neq 0 \end{aligned}}$ → D-I-Y

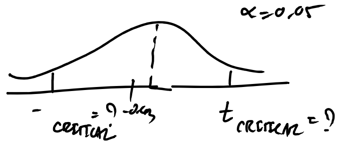
$H_0: \delta_1 = 0$

$H_1: \delta_1 \neq 0$

Either t-test or F-test can be employed

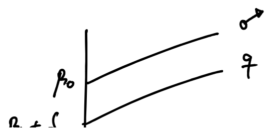
$$\hat t = \frac{-0.0056}{0.0131} = -0.43$$

$\alpha = 0.05$



Since $\hat t$ falls into acceptance region, then we fail to reject $H_0: \delta_1 = 0$.

Therefore, there is no difference in ROE between men and women. (DIFFERENT INTERCEPT BUT SAME SLOPE)



SAME SLOPE)