

Chapter 6: Further Issues in MLR

①

Incorporating Nonlinearities (see Chapter 2 pp. 43-44)

So far we have focused on linear relationships between the dependant and independent variables. Sometimes this is not general enough.

One important possibility is when the dependant variable is in logarithmic form:

$$\log(y) = \beta_0 + \beta_1 x_1 + u$$

Recall the wage-education example, where we obtained a slope estimate of $\hat{\beta}_1 = 0.54$, which means that each additional year of education is predicted to increase hourly wage by 54¢. This is the same for the first year of education and the 12th year of education. (or the 100th year). This may not be reasonable.

A better characterization of how wages change maybe that each year of education increases wage by a constant percentage.

For example, increasing education from 5 to 6 years, ceteris paribus, increases wages by 8% as does an increase from

~~10 to 11~~ 11 to 12 years of education.

A model that gives (approx.) a constant percentage effect is

$$\log(\text{wage}) = \beta_0 + \beta_1 \text{educ} + u$$

In particular, if $\Delta u = 0$, then

$$\% \Delta \text{wage} \approx (100 \cdot \beta_1) \Delta \text{educ}$$

Note: we multiply β_1 by 100 to get the percentage change in wage given one additional year of education. Since the percentage change in wage is the same for each extra year of educ this gives us an increasing return to education.

Models with Quadratics

Quadratic functions are used quite a bit in applied econometrics to capture decreasing or increasing marginal effects.

In the simplest case

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + u$$

For example, let $y = \text{wage}$ and $x = \text{exper.}$ β_1 does not (now) measure the change in y with respect to x , because it makes no sense to hold x^2 fixed while changing x .

Writing the estimated equation: we have

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{\beta}_2 x^2$$

then we have the approximation

$$\Delta \hat{y} \approx (\hat{\beta}_1 + 2\hat{\beta}_2 x) \Delta x \quad \text{so}$$

$$\frac{\Delta \hat{y}}{\Delta x} \approx \hat{\beta}_1 + 2\hat{\beta}_2 x$$

This means that the slope of the relationship between x and y depends on the value of x (estimated slope is $\hat{\beta}_1 + 2\hat{\beta}_2 x$)

If we plug in $x=0$, $\hat{\beta}_1$ can be interpreted as the approx. slope going from $x=0$ to $x=1$. After that the second term $2\hat{\beta}_2 x$ must be accounted for

Ex:

$$\text{Wage} = \underset{(.35)}{3.73} + \underset{(.0411)}{.298 \text{ exper}} - \underset{(.0009)}{.0061 \text{ exper}^2}$$

$$n = 526, R^2 = .093$$

This implies that exper has a diminishing effect on wage.

The first year of experience is worth roughly 30¢ per hour (\$.298)

The second is worth less [.298 - 2(.0061)(1) \approx .286 or 28.6¢]

From 10 to 11 years of experience wage is predicted to increase by about .298 - 2(.0061)(10) = .176 or 17.6¢

And so on.

~~With~~ With $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ the turning point is achieved at

$$X^* = \left| \frac{\hat{\beta}_1}{2\hat{\beta}_2} \right|$$

Models with Interaction Terms

Sometimes the partial effect of the dependant variable with respect to an explanatory variable may depend on another explanatory variable.

For example, consider the model

$$\text{price} = \beta_0 + \beta_1 \text{sqft} + \beta_2 \text{bedrms} + \beta_3 \text{sqft} \cdot \text{bedrms} + \beta_4 \text{bthrms} + u$$

the partial effect of bedrooms on price (hold all else fixed) is

$$\frac{\Delta \text{price}}{\Delta \text{bedrms}} = \beta_2 + \beta_3 \text{sqft}$$

If $\beta_3 > 0$ then an additional bedroom yields a higher increase in housing price for larger houses.

More on goodness-of-Fit

We mentioned that adding an additional (or many additional) explanatory variables can never decrease the R^2 . We want a measure that in some sense penalizing for adding additional variables. Then if that new measure increases when an additional variable is added we can be more certain that it is because it is helpful in explaining the variation in y ! This is the adjusted R^2 :

$$R^2_{adj} = \frac{SSR}{(n-k-1)} \div \frac{SST}{(n-1)}$$

oops



$$\begin{aligned}\bar{R}^2 &= 1 - [SSR / (n-k-1)] / [SST / (n-1)] \\ &= 1 - \hat{\sigma}^2 / [SST / (n-1)]\end{aligned}$$

or in terms of R^2

$$\bar{R}^2 = 1 - (1 - R^2)(n-1) / (n-k-1)$$

Chapter 7: MLR with Qualitative Information

Sometimes we want to incorporate qualitative information into our models. Consider

$$\text{Wage} = \beta_0 + \delta_0 \text{female} + \beta_1 \text{educ} + u$$

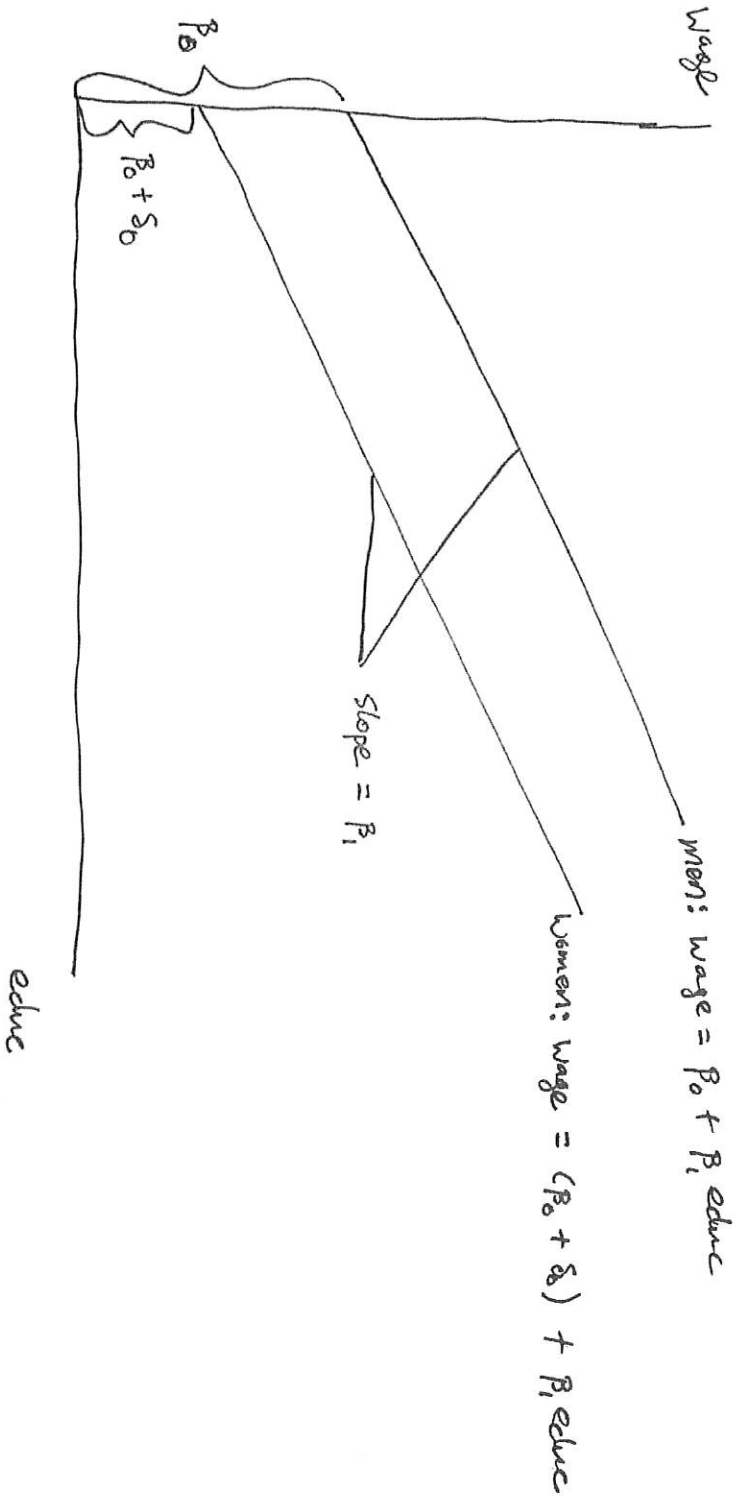
Where female is a binary variable equal to 1 if individual i is a female and 0 otherwise.

The parameter δ_0 has the following interpretation:

δ_0 is the difference in hourly wages between males and females, given the same amount of education.

Thus δ_0 determines if there is discrimination. If $\delta_0 < 0$ then, for the same level of other factors, women earn less than men on average.

Graphically



Avoiding the Dummy Variable Trap

Including two binary variables, say $\text{female} = \begin{cases} 1 & \text{if female} \\ 0 & \text{if male} \end{cases}$

and $\text{male} = \begin{cases} 0 & \text{if female} \\ 1 & \text{if male} \end{cases}$ would introduce

perfect collinearity because $\text{female} + \text{male} = 1$, which means the male is a perfect linear function of female.

Including the both is called the dummy variable trap.

(4)

When we in the binary variable females in wage regression we have chosen males as the base group or benchmark group.

This is the group against which comparisons are made. That is why β_0 is the intercept for males and δ_0 is the difference between males and females.

We could have just as easily written the model

$$\text{Wage} = \alpha_0 + \delta_0 \text{ males} + \beta_1 \text{educ} + u$$

in which case females would be the base group, and α_0 would be the intercept for females and δ_0 would be the difference between females and males.

We can put binary variables in the MLR as, for example (5)

$$\text{wage} = \beta_0 + \beta_1 \text{educ} + \beta_2 \text{exper} + \beta_3 \text{female} + \delta_0 \text{female} + u$$

We can test for no difference between males and females with a t test with

$$H_0: \delta_0 = 0$$

$$H_1: \delta_0 < 0$$

Rejecting H_0 would suggest there is evidence of discrimination.