LECTURE 7

Introduction to Econometrics

Nonlinear specifications and dummy variables

October 27, 2017

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- We will define the notion of a dummy variable and we will show its different uses in linear regression models

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  - Do we expect a curve instead of a straight line? Does the effect of a variable peak at some point and then start to decline?

LINEAR FORM

Linear form

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- Linear form is used as default functional form until strong evidence that it is inappropriate is found

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- Before using a double-log model, make sure that there are no negative or zero observations in the data set

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  - Ceteris paribus is a Latin phrase meaning 'other things being equal'.

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EXAMPLES OF SEMILOG FORMS

Examples of semilog forms

- Estimating demand for chicken meat:

$$\widehat{Y} = -6.94 - \underset{(0.19)}{0.57}\ PC + \underset{(0.11)}{0.25}\ PB + \underset{(2.81)}{12.2}\ \ln YD$$

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- Interpretation: An increase in the annual disposable income by 1% increases chicken consumption by 0.12 kg per year, ceteris paribus.

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- Estimating the influence of education and experience on wages:

$$\widehat{\ln wage} = 0.217 + \underset{(0.008)}{0.098}\, educ + \underset{(0.002)}{0.010}\, exper$$

wage	...	annual wage (USD)
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- Interpretation: An increase in education by one year increases annual wage by 9.8%, ceteris paribus. An increase in experience by one year increases annual wage by 1%, ceteris paribus.

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- We might also have higher order polynomials, e.g.:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_1^3 + \beta_4 x_1^4 + \varepsilon$$

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  - Decreasing returns to hours of studying: more hours implies higher grade, but the positive effect of additional hour of studying decreases with more hours

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  - Remember that one of the OLS assumptions is that the model is correctly specified
- Ideally: the specification is given by underlying theory of the equation
- In reality: underlying theory does not give precise functional form
- In most cases, either linear form is adequate, or common sense will point out an easy choice from among the alternatives

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  - R^2 is incomparable across models where the y is transformed
  - dependent variables are often transformed to log-form in order to make their distribution closer to the normal distribution

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$$Male = \begin{cases} 1 & \text{if the person is male} \\ 0 & \text{if the person is female} \end{cases}$$

$$Weekend = \begin{cases} 1 & \text{if the day is on weekend} \\ 0 & \text{if the day is a work day} \end{cases}$$

$$NewStadium = \begin{cases} 1 & \text{if the team plays on new stadium} \\ 0 & \text{if the team plays on old stadium} \end{cases}$$

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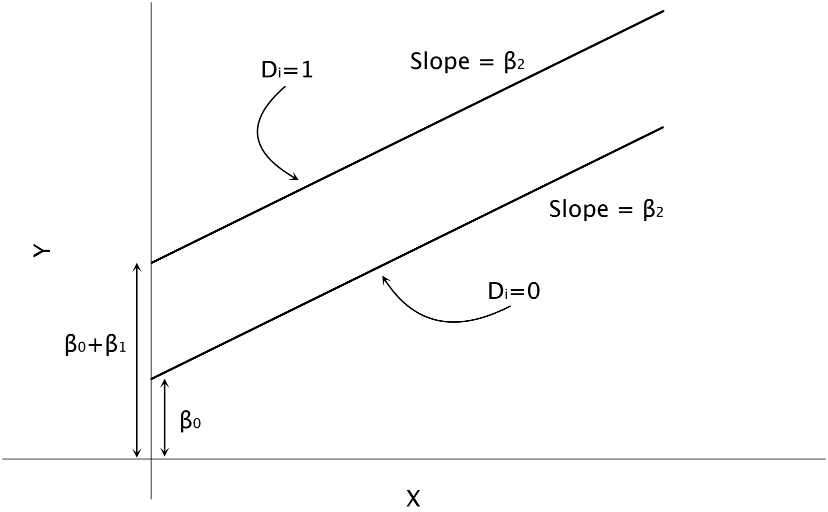

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where $\quad M_i = \begin{cases} 1 & \text{if the } i\text{-th person is male} \\ 0 & \text{if the } i\text{-th person is female} \end{cases}$

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- Interpretation of the dummy variable M: men earn on average \$2.156 per hour more than women, ceteris paribus

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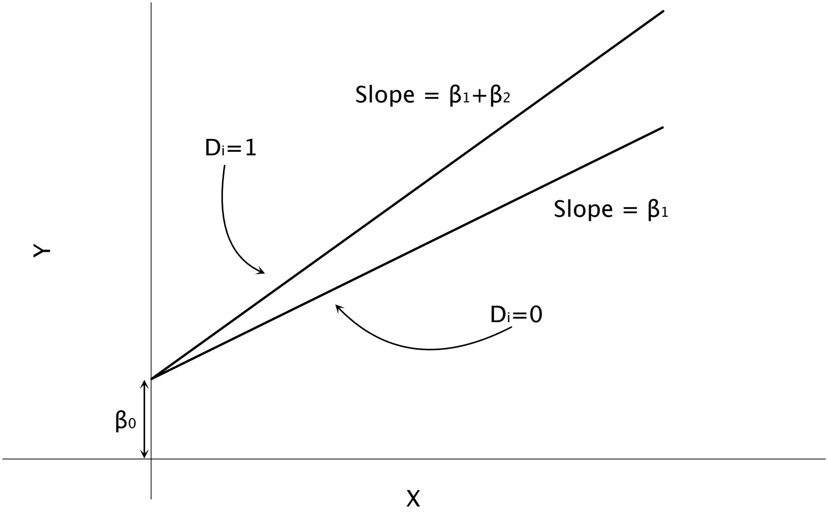

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- Interpretation: men gain on average 17 cents per hour more than women for each additional year of education, ceteris paribus

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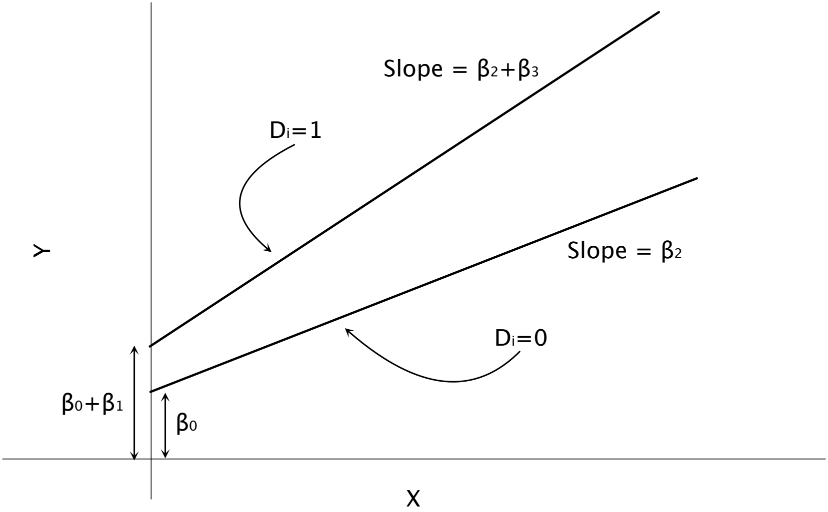

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  - Using full set of dummies leads to perfect multicollinearity (dummy variable trap, see next lectures)

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- Further readings:
    - Studenmund, Chapter 7
    - Wooldridge, Chapters 6 & 7