

POLS 6481. Research Design and Quantitative Methods II

Lecture 21. Polynomial Functional Forms I: Coefficients and Marginal Effects

Readings: Wooldridge, *Introductory Econometrics 5e*, 6.2b + 9.1

Outline

1. Monomial Nonlinear Specifications (Dougherty, *Introduction to Econometrics*, ch. 4)
2. Polynomial Nonlinear Specifications
3. Example: Wages and experience
4. Combining Logarithms and Quadratics

Lecture 21 = *focus on the 'numerator' (coefficients, marginal effects)*

Lecture 22 = *focus on the 'denominator' (standard error) and 'ratio' (t statistic)*

1. Monomial Nonlinear Specifications

Three functional forms discussed in “Nonlinear Models and Transformation of Variables”

1. Reciprocal (hyperbola) $y = \beta_0 + \beta_1 \frac{1}{x} + u = \beta_0 + \beta_1 x^{-1} + u$
2. Radical $y = \beta_0 + \beta_1 \sqrt{x} + u = \beta_0 + \beta_1 x^{.5} + u$
3. Exponential** $y = \beta_0 + \beta_1 \log(x) + u$

These three functional forms: manipulate the **right hand side** of the regression equation;
are linear in the parameters (β_0 and β_1);
have additive disturbance (u),** and therefore are best
suited to situations where y is normally distributed.

(If time is available, take some first derivatives on this slide and the next slide...)

** Model 3 looks like a level-log model, but it can be rewritten: $e^y = f(x, u) = e^{\beta_0} \cdot x^{\beta_1} \cdot v$,
where $v = e^u$

2. Polynomial Nonlinear Specifications

Three kinds of polynomial models for $y = f(x)$:

	Linear	Quadratic	Cubic*
equation	$y_i = \beta_0 + \beta_1 x_i + u_i$	$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + u_i$	$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + u_i$
graph	line	parabola (convex/concave)	S-curve (convex & concave)
effect of Δx	$\frac{\Delta y}{\Delta x} = \beta_1$ (constant)	$\frac{\Delta y}{\Delta x} = \beta_1 + 2\beta_2 x_i$ (conditional on x)	$\frac{\Delta y}{\Delta x} = \beta_1 + 2\beta_2 x_i + 3\beta_3 x_i^2$ (conditional on x)
vertices?	none	one at $x^* = -\frac{\beta_1}{2\beta_2}$	three
slope	positive if $\beta_1 > 0$	both positive and negative (equals 0 at vertex)	both positive and negative (equals 0 once, twice, thrice)

* the “cubic spline” models are cubic but not polynomial

3. Example: Wages and experience

Linear regression model: $\widehat{wage} = 5.37 + .03 \cdot exper$
(.26) (.01)

Marginal effect: $\frac{\partial wage}{\partial exper} = .03$

Note that when Wooldridge uses WAGE1 dataset in chapters 2–4, he usually uses $\log(wage)$ as the dependent variable and/or uses $educ$ as the key explanatory variable.

```
library(foreign); data <- read.dta("C:/WAGE1.dta")
linear <- lm(wage ~ exper, data); summary(linear)$coefficients
plot(data$exper, data$wage, pch=19, cex=.67); abline(linear, col="deepskyblue", lwd=3)
summary(linear)$r.squared
```

```
quad <- lm(wage ~ exper + expersq, data); summary(quad)$coefficients
summary(quad)$r.squared
```

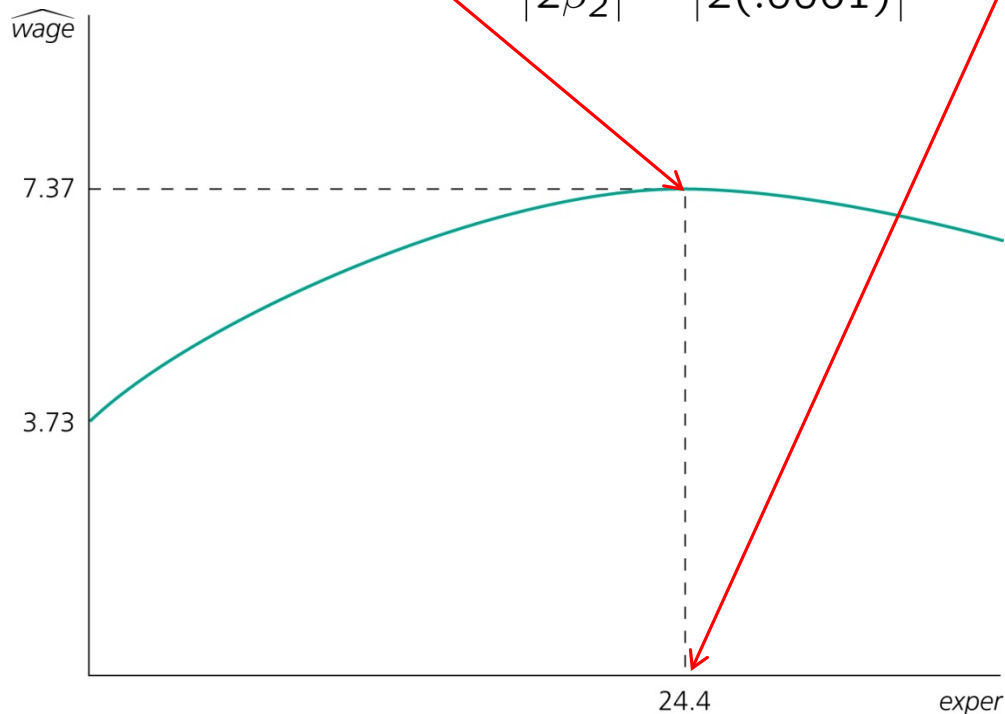
--> remember the F test for adding the squared-experience term

3. Example: Wages and experience

Quadratic regression model: $\widehat{wage} = 3.73 + .298 \text{ exper} - .0061 \text{ exper}^2$
(.35) (.041) (.0009)

Marginal effect: $\frac{\partial \widehat{wage}}{\partial \text{exper}} = .298 - 2(.0061)\text{exper}$

Turning point: $x^* = \left| \frac{\hat{\beta}_1}{2\hat{\beta}_2} \right| = \left| \frac{.298}{2(.0061)} \right| \approx 24.4$



4. Combining Logarithms and Quadratics

Rules for interpreting coefficients with logged dependent variables:

Log-level $\log(y)$ x $\% \Delta y = (100 \cdot \beta_1) \Delta x$

A one-unit change in x leads to *approximately* a $100 \cdot \beta_1$ percent change in y

Log-log $\log(y)$ $\log(x)$ $\% \Delta y = \beta_1 \cdot \% \Delta x$

A one-percent change in x leads to a β_1 percent change in y

Rule for calculating marginal effects in quadratic models:

Model: $\log(y_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + u_i$

Marginal Effects: $\frac{\Delta \log(y)}{\Delta x} = \beta_1 + 2\beta_2 x_i \quad \rightarrow \quad \frac{\% \Delta y}{\Delta x} = 100 \cdot (\beta_1 + 2\beta_2 x_i)$

Vertex: marginal effect = 0 when $x = -\frac{\beta_1}{2\beta_2}$

4. Combining Logarithms and Quadratics

Examples 4.5, 6.1, and 6.2 use HPRICE2 dataset; sample is 506 communities in Boston area.

price is community's median housing price; *rooms* is community's mean # rooms in houses.

nox is a measure of air pollution (nitrogen oxide); 1% ↑ in air pollution → .71% ↓ in price

$$\log(\text{price}) = 9.23 - .713 \log(\text{nox}) + .306 \text{rooms} \quad [6.7]$$

(.19) (.066) (.019)

$$\Rightarrow \frac{\partial \log(\text{price})}{\partial \text{rooms}} = \frac{\% \partial \text{price}}{\partial \text{rooms}} = + .306 \quad \text{Increase rooms by 1: + 30.6\% price}$$

On p. 197 (in 5th ed) Wooldridge states that coefficient for *rooms* is + .255 when two control variables added: *log(dist)* is weighted distance of community from five employment centers; *stratio* is average student-teacher ratio of schools in community. See p. 132–3 (in 5th ed):

$$\log(\text{price}) = 11.08 - .954 \log(\text{nox}) + .255 \text{rooms} - .134 \log(\text{dist}) - .052 \text{stratio}$$

(.32) (.117) (.019) (.043) (.006)

$$\Rightarrow \frac{\partial \log(\text{price})}{\partial \text{rooms}} = \frac{\% \partial \text{price}}{\partial \text{rooms}} = + .255 \quad \text{Increase rooms by 1: + 25.5\% price}$$

4. Combining Logarithms and Quadratics

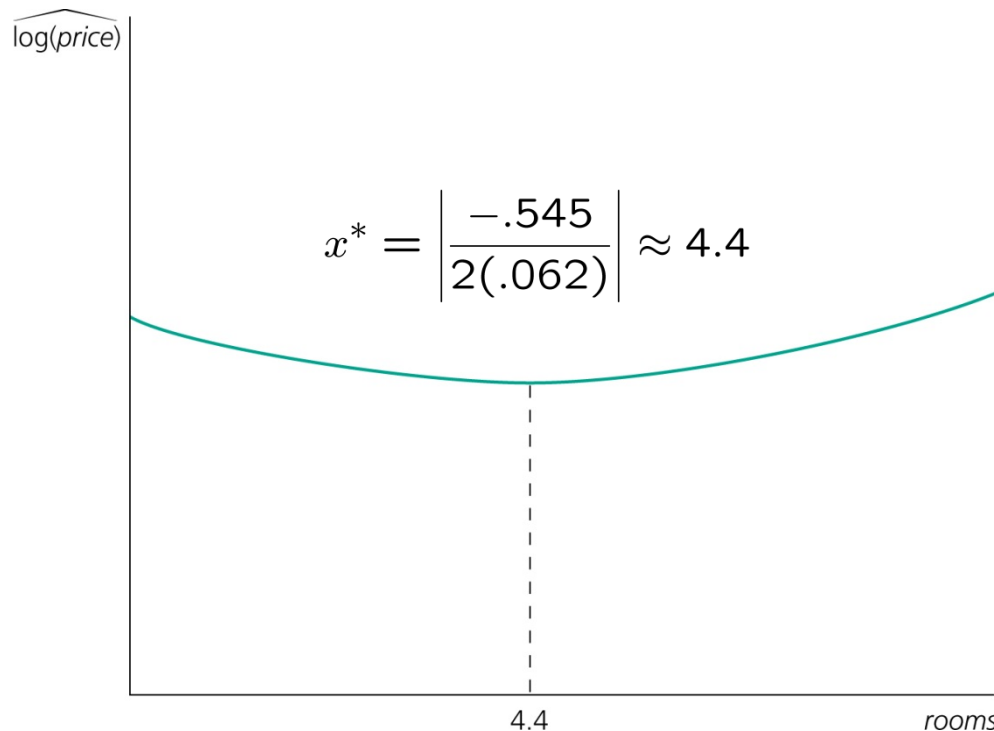
$$\widehat{\log(price)} = 13.39 - .902 \log(nox) - .087 \log(dist) \quad [6.14b]$$

$$- .545 \text{ rooms} + .062 \text{ rooms}^2 - .048 \text{ stratio}$$

$$(.57) \quad (.115) \quad (.043)$$

$$(.165) \quad (.013) \quad (.006)$$

$$\Rightarrow \frac{\partial \log(price)}{\partial \text{rooms}} = \frac{\% \partial price}{\partial \text{rooms}} = -.545 + .124 \text{ rooms}$$



Increase # rooms from 5 to 6:

$$-.545 + .124(5) = +7.5\% \text{ price}$$

Increase # rooms from 6 to 7:

$$-.545 + .124(6) = +19.9\% \text{ price}$$

Increase # rooms from 7 to 8?

p. 198 (in 5th ed) gets silly: including a squared-logged term, for example