advanced measurement (logs, quadratics)

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<u>outline</u>

interpretation: transforming variables

- \diamond Lin: One unit change in X leads to a β_2 unit change in Y.
- \diamond Log-Lin: One unit change in X leads to a $100 * \beta_2$ % change in Y. (guj ed4:p180 fig6.4; ed5:p163 ex6.4)
- \diamond Lin-Log: One percent change in X leads to a $\beta_2/100$ unit change in Y. (guj: ed4:p182 fig6.5; ed5:p165-6 ex6.5)
- ♦ Log-Log (aka log-linear or "linear in logs"): One percent change in X leads to a β_2 % change in Y (elasticity).

logs practice

https://stats.idre.ucla.edu/other/mult-pkg/faq/general/ faqhow-do-i-interpret-a-regression-model-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-some-varianterpret-a-regression-when-y-regression-when-y-regression-when-y-regression-when-y-regressio

♦ http://www-stat.wharton.upenn.edu/~stine/stat621/handouts/LogsInRegression.pdf

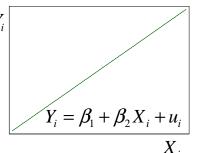
natural logarithm; for simplicity just log or In

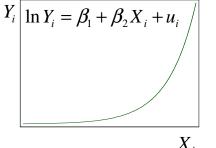
- ♦ log() or ln(), to reverse it exp()
- ♦ it tells us how many times 2.72 was multiplied, eg:
- o log(7.4) = 2, because $2.72^2 = 7.4$
- $oldsymbol{log} log(22166) = 10$, because $2.72^{10} = 22166$
- it compresses distribution!
- it makes very big numbers relatively small https://en.wikipedia.org/wiki/Wheat_and_chessboard_problem
- o it is often used to remove outliers
- o say wage, prices, any \$ amounts are very skewed
- o and log will make them more normally distributed

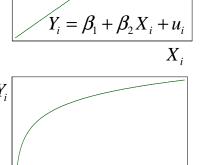
log makes cool interpretations in regressions

- again it makes very big numbers small
- actually, the bigger the number, the much more it is compressed
- $\circ \log(10) \approx 2$; $\log(100) \approx 4$; $\log(1000) \approx 7$; $\log(10,000) \approx 9$
- what you think will happen if you log transform your x?
- as the values of x increase, the effect on Y would be weaker
- o originally huge differences at high levels of X are now tiny
- what if we log transform Y variable? the other way round!
- o so the effect of X would be increasing

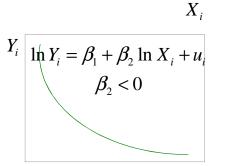
it makes a difference







 $|Y_i = \beta_1 + \beta_2 \ln X_i + u_i|$



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lin-lin [dofile: measurement]

- eg more education earn higher wages
- $\diamond Y_i = \beta_1 + \beta_2 X_i + u_i$
- the change is constant regardless of the level of X
 (because β is constant)
- \diamond wage_i = $\beta_1 + \beta_2$ educ_i + u_i
- $\circ \widehat{wage}_i = -0.75 + 0.75 educ_i$
- $\circ \widehat{wage}_{10} = \$6.75 \quad \widehat{wage}_{11} = \$7.50 \quad \Delta \widehat{wage} = \0.75 the change is the same for any 1 year change in educ

relative change: log-lin

- ♦ take log of Y first, then regress InY on X
- regression treats InY the same as any other var
- o percent change in Y per unit change in X is
- \circ 100* β_2 times the unit change in X (for small changes)
- still a linear regression, but with a new DV: InY.
- o not linear in terms of Y

eg log-lin [dofile: measurement]

- $\Rightarrow ln(wage_i) = \beta_1 + \beta_2 educ_i + u_i$
- $hltitle In(wage)_i = 1.06 + 0.08educ_i$
- this is the predicted In(wage)
- o but what about the predicted wage?
- $\Rightarrow \widehat{wage}_{10} = e^{1.86} = \6.42 exp()
- $\Rightarrow \widehat{wage}_{11} = e^{1.94} = \6.96
- $0.08 = \frac{10.96 10.42}{10.42} = \frac{10.96 10.42}{10.42} = 0.08 = \frac{10.96}{10.42} = 0.08 = \frac{10.96}{10.42} = 0.08 = \frac{10.96}{10.42} = 0.08 = \frac{10.96}{10.42} = \frac{10.96} = \frac{10.96}{10.42} = \frac{10.96}{10.42} = \frac{10.96}{10.42} = \frac{$

the change varies in dollar terms

- but let's examine the change in wage for an additional year of graduate school, eg master's degree years.
- $\phi \ \widehat{ln(wage)_i} = 1.06 + 0.08educ_i$
- $\Rightarrow ln(wage)_{17} = 1.06 + 0.08(17) = 2.42 \quad \widehat{wage}_{17} = \11.25
- $\Rightarrow ln(wage)_{17} = 1.06 + 0.08(18) = 2.50 \quad \widehat{wage}_{18} = 12.18
- $\diamond \ \%\Delta \widehat{wage}_{17\rightarrow 18} = 0.08 = 8\%$
- the change in relative (percentage) terms is constant at
 0.08 (8 percent), but the dollar change is larger.

lin-log [dofile: measurement]

- $\diamond Y_i = \beta_1 + \beta_2 \ln X_i + u_i$
- we generate the natural log of education and regress dollar wage on the log of education

eg: lin-log

- wage as a function of relative change in education
- \diamond wage_i = $\beta_1 + \beta_2 ln(educ_i) + u_i$
- $\Rightarrow \widehat{wage}_i = -10.15 + 7.54 ln(educ_i)$
- $\diamond \ \widehat{wage}_{10} = -10.15 + 7.54 \ln(10) = 7.21$
- $\diamond \ \widehat{wage}_{11} = -10.15 + 7.54 \ln(11) = 7.93$
- $\diamond \ \%\Delta \widehat{wage}_{10\rightarrow 11} = \0.72
- $\Rightarrow \widehat{wage}_{17} = -10.15 + 7.54 \ln(17) = 11.21$
- $\diamond \ \widehat{wage}_{18} = -10.15 + 7.54 ln(18) = 11.64$
- $\diamond \ \%\Delta \widehat{wage}_{17\rightarrow 18} = \0.43
- \diamond for a 1% (0.01) change in X, the change in Y is $\beta_2/100$, in this case 0.0754

relative change in education

educ	%	change	educ	%change	
	1			11	10%
	2	100%		12	9%
	3	50%		13	8%
	4	33%		14	8%
	5	25%		15	7%
	6	20%		16	7%
	7	17%		17	6%
	8	14%		18	6%
	9	13%		19	6%
	10	11%		20	5%

relative change in

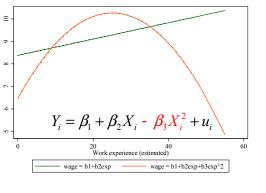
education per year is declining because the base is getting larger. Lin-log will predict a smaller impact on wage each year (see graph few slides back)

quadratic regression

- does what logs do-fits a curve as opposed to a line
- i think more intuitive than logs
- the idea is that quadratic coef is smaller than linear, and opposite sign
- but as X gets bigger, its square get huge, and so quadratic coef with opposite sign overpowers first term and curve flips to positive or negative

quadratic model

If a *non-linear relationship* between *X* and *Y* is suspected, a *polynomial function of X* can be used to model it.

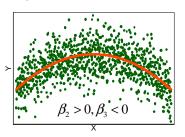


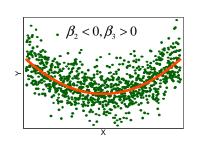
when it flips:

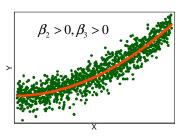
$$X_i^* = -\frac{\beta_2}{2\beta_3}$$

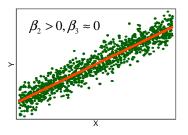
This curve reaches a maximum wage at the point were the marginal effect of experience is zero.

quadratic model









quadratic: interpretation

- ⋄ the slope changes with X, it is not constant
- best graph it
- there is always a tipping point, but it may be outside the range of the data; in fact, the estimated line may be approximately linear for the observed data range even if the quadratic term is significant!
- t test on squared term has a null hypothesis of linearity
 if it is not significant, only linear term is left
- ♦ dofile: quadratic,bonus
- btw most general is dummies; esp if sth like yrs of educ: neither log or quadratic, but dummy out (next week) esp level completion at 12,16 etc