POLS 6481. Research Design and Quantitative Methods II

Lecture 23. Binary Independent Variables I: Different Intercepts for Different Groups

Readings: Wooldridge, *Introductory Econometrics 5e*, 7.1 + 7.2a + 7.3 (+ 4.2 + 4.4) + 17.3

Outline

1. A Single Dummy in a Regression
2. Multiple Dummies for a Single Dimension in a Regression
3. Hypothesis Testing for Unidimensional Dummies
4. Example: *'Looking Good on Course Evaluations' part 2*
5. Review of Poisson Probability Distribution & Poisson Regression
6. Example: *Economic Model of Crime*

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1. A Single Dummy in a Regression

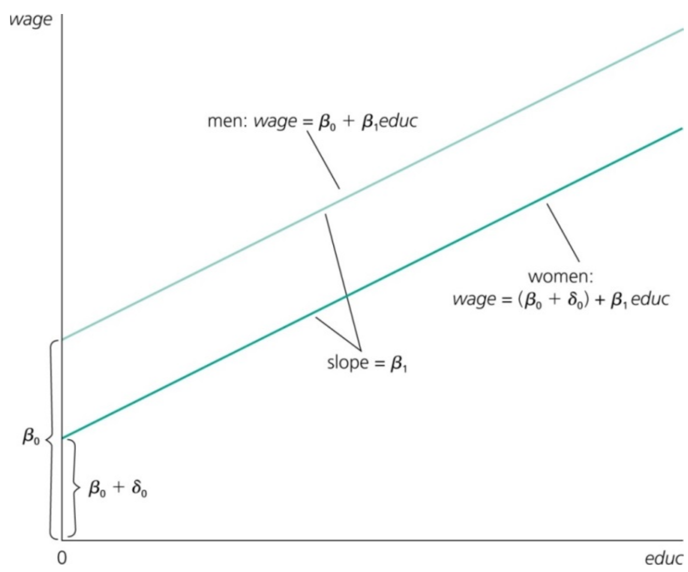
Combined model: $wage = \beta_0 + \delta_0 \cdot female + \beta_1 educ + u$

men only: $wage = \beta_0 + \beta_1 educ + u$

women only: $wage = (\beta_0 + \delta_0) + \beta_1 educ + u$

Intercept shift interpretation: $E(wage \mid female{=}1, educ = 0) = \beta_0 + \delta_0$

$E(wage \mid female{=}0, educ = 0) = \beta_0$



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1. A Single Dummy in a Regression

Combined model: $wage = \beta_0 + \delta_0 \cdot female + \beta_1 educ + u$

men only: $wage = \beta_0 + \beta_1 educ + u$

women only: $wage = (\beta_0 + \delta_0) + \beta_1 educ + u$

Treatment effect interpretation: $\delta_0 = \mathrm{E}(wage \mid female{=}1, educ) - \mathrm{E}(wage \mid female{=}0, educ)$

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1. A Single Dummy in a Regression

Example: *Gender and Wages* (Wooldridge Example 7.1; use WAGE1.DTA)

Practical effect of adding control variables:

$$\begin{aligned}\widehat{wage} &= \underset{(.21)}{7.10} - \underset{(.30)}{2.51}\, female \\ n &= 526,\ R^2 = .116.\end{aligned} \qquad [7.5]$$

$$\begin{aligned}\widehat{wage} &= \underset{(.72)}{-1.57} - \underset{(.26)}{1.81}\, female + \underset{(.049)}{.572}\, educ + \underset{(.012)}{0.25}\, exper + \underset{(.021)}{.141}\, tenure \\ n &= 526,\ R^2 = .364.\end{aligned} \qquad [7.4]$$

Adding education, experience and tenure helps avoid omitted variable bias – if women have lower values of these variables than men, on average. (Look back at equations for OVB; if *female* is negatively correlated to *educ*, *exper*, *tenure*, then …)

Adding education, experience and tenure improves model fit and reduces standard errors, even after accounting for how correlation among indep. variables inflates standard errors.

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1. A Single Dummy in a Regression – some comments

Note 1: 👍 regression analysis replaces ANOVA and ANCOVA for modeling control group versus experimental/treatment group(s)

Note 2: 👌 changing base/benchmark group (sign of *t* reverses)

Note 3: 👎 a 'dummy' variable with no theoretical meaning… e.g., American 'exceptionalism'

Note 4: ☠ Caution about endogenous treatment selection… e.g., challenger 'quality'

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2. Multiple Dummies for a Single Dimension in a Regression

Consider an *ordinal* explanatory variable…

e.g., cities' and local governments' credit ratings (0 = worst, …, 4 = best) [p. 237–238, 5th ed.]

Option A. regress municipal bond ratings on a single variable ($CR \in \{0, 1, 2, 3, 4\}$)…

$$MBR = \beta_0 + \beta_1 CR + \textit{other factors}$$

… but this assumes the ratings equal-interval property is satisfied.

Option B. regress municipal bond ratings on four dummies:

$$MBR = \beta_0 + \delta_1 CR_1 + \delta_2 CR_2 + \delta_3 CR_3 + \delta_4 CR_4 + \textit{other factors}.$$

If there were data available, then one could use an F test to compare model fit with 1 variable with k values (Option A) vs. k–1 dummies (Option B); refer back to Lecture on 'ANOVA for Regression Specifications'

2. Multiple Dummies for a Single Dimension in a Regression

Consider an *ordinal* explanatory variable…

e.g., how law students' starting salaries depending on rankings [Example 7.8, 239–40]:

$$\widehat{\log(salary)} = \underset{(.41)}{9.17} + \underset{(.053)}{.700}\, top10 + \underset{(.039)}{.594}\, r11\_25 + \underset{(.034)}{.375}\, r26\_40 + \underset{(.028)}{.263}\, r41\_60 + \underset{(.021)}{.132}\, r61\_100 + \underset{(.0031)}{.0057}\, LSAT$$

$n = 136$, $R^2 = .911$,

Use dataset lawsch85.dta and see R script: Lecture 23A law students

Use an F test to compare fit using 1 variable with 6 values vs. 5 dummies
$df_r = 133 = 136 - 3$ (constant, *LSAT*, one ordinal variable)
$df_u = 129 = 136 - 7$ (constant, *LSAT*, five binary variables)
$q = df_r - df_u = 4$

$$F = \frac{\left(R_u{}^2 - R_r{}^2\right)/4}{\left(1 - R_u{}^2\right)/129}$$

Don't forget the rule for interpreting marginal effects in a log-linear model: the *percentage* change in salary for group j, relative to baseline group, $= 100 \cdot \left(e^{\delta_j} - 1\right)$

3. Hypothesis Testing for Unidimensional Dummies – Review [4.2]

Null hypothesis: $H_{0j} : \beta_j = 0$

Alternative hypothesis: $H_{1j} : \beta_j \neq 0$

Test statistic: $t = \dfrac{\widehat{\beta_j}}{se(\widehat{\beta_j})}$

The t statistic answers the question: How many standard errors separate the estimated coefficient ($\widehat{\beta}_j$) from the null hypothesis (0) for the coefficient?

Values of the t statistic sufficiently far from 0 result in a rejection of H_{0j} ;
our **rejection rule** is to reject H_{0j} if and only if $\left|t_{\widehat{\beta_j}}\right| > c$;
by convention, c is chosen to make areas above $+c$ and below $-c$ sum to .05

If H_{0j} is rejected at the 5% level, then we conventionally say "x_j is statistically significant."

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3. Hypothesis Testing for Unidimensional Dummies – Review [4.2]

Null hypothesis: $H_{0j} : \beta_j = a_j$

Alternative hypothesis: $H_{1j} : \beta_j \neq a_j$

Test statistic: $$t = \frac{(estimate - hypothesized\ value)}{standard\ error\ of\ estimate} = \frac{(\widehat{\beta_j} - a_j)}{se(\widehat{\beta_j})}$$

The t statistic answers the question: How many standard errors separate the estimated coefficient ($\widehat{\beta_j}$) from the null hypothesis (a_j) for the coefficient?

Values of the t statistic sufficiently far from 0 result in a rejection of H_{0j} ;
our **rejection rule** is to reject H_{0j} if and only if $\left|t_{\widehat{\beta_j}}\right| > c$;
by convention, c is chosen to make areas above $+c$ and below $-c$ sum to .05

If H_{0j} is rejected at the 5% level, then we conventionally say "x_j is statistically significant."

3. Hypothesis Testing for Unidimensional Dummies [4.4]

Null hypothesis: $H_0 : \beta_1 - \beta_2 = 0$ (equivalent to $H_0 : \beta_1 = \beta_2$)

Alternative hypothesis: $H_1 : \beta_1 - \beta_2 \neq 0$ (equivalent to $H_1 : \beta_1 \neq \beta_2$)

Test statistic is $t = \dfrac{difference\ of\ coefficients}{standard\ error\ of\ difference\ \ldots} = \dfrac{\widehat{\beta_1} - \widehat{\beta_2}}{se\left(\widehat{\beta_1} - \widehat{\beta_2}\right)}$

where $se(\hat{\beta}_1 - \hat{\beta}_2) = \sqrt{\widehat{Var}(\hat{\beta}_1 - \hat{\beta}_2)} = \sqrt{\widehat{Var}(\hat{\beta}_1) + \widehat{Var}(\hat{\beta}_2) \boxed{- 2\widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)}}$

$$= \sqrt{\left[\widehat{Var}(\hat{\beta}_1) - \widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)\right] + \left[\widehat{Var}(\hat{\beta}_2) - \widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)\right]}$$

Readings: Wooldridge, *Introductory Econometrics 5e*, 7.1 + 7.2a + 7.3 (+ 4.2 + 4.4) + 17.3

4. Example: *'Looking Good on Course Evaluations' part 2*

http://chance.amstat.org/2013/04/looking-good/
Data: eval.csv
Script: Lecture 23A evaluations.R

Dependent variable is average evaluation of professor, prof_eval (0 – 5 scale; mean = 4.175)

Explanatory variable is average attractiveness bty_avg (range = 1.667 – 8.167; mean = 4.418)

"Level one" control variables:
age (quantitative)
gender (binary; *female* or *male*)
language (binary; *English* or *non-English*)
ethnicity (binary; *minority* or *not minority*)
rank (qualitative; *teaching* and *tenure track* and *tenured*)

"Level two" variables:
six different raters (three male, three female)
thirty classes (class1, …, class30)
cls_level (binary; *lower* division or upper division)

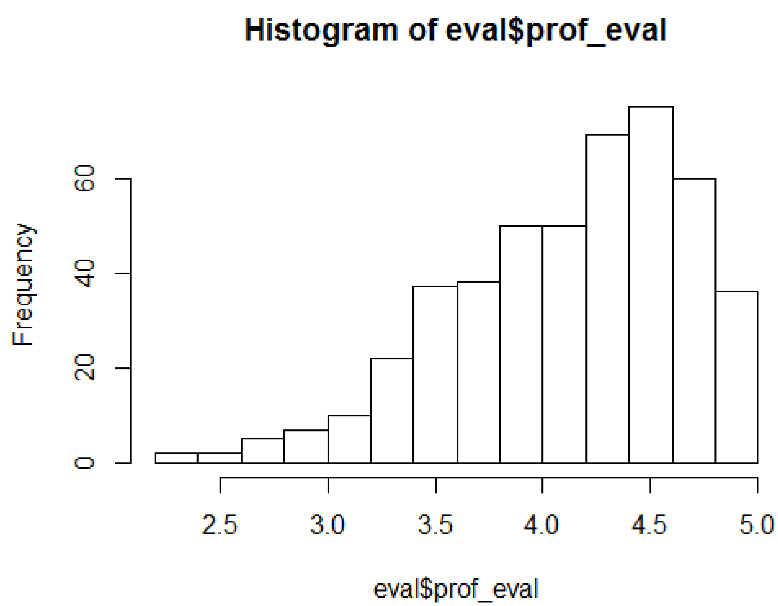
4. Example: *'Looking Good on Course Evaluations' part 2*

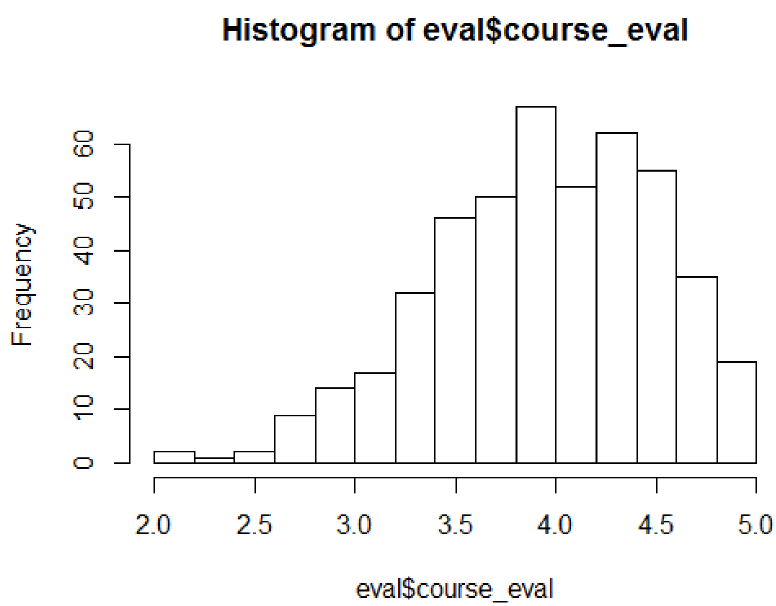
http://chance.amstat.org/2013/04/looking-good/

Data: eval.csv

Script: Lecture 23A evaluations.R

Dependent variable is average evaluation of professor (0 – 5 scale; mean = 4.175)
[average evaluation of course (0 – 5 scale; mean = 3.998)]





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4. Example: *'Looking Good on Course Evaluations' part 2*

Consider the effects of rank ("teaching" and "tenure track" and "tenured")
Dependent variable is average evaluation of professor (0 – 5 scale; mean = 4.175)

Without control for attractiveness (R^2 = .0116):

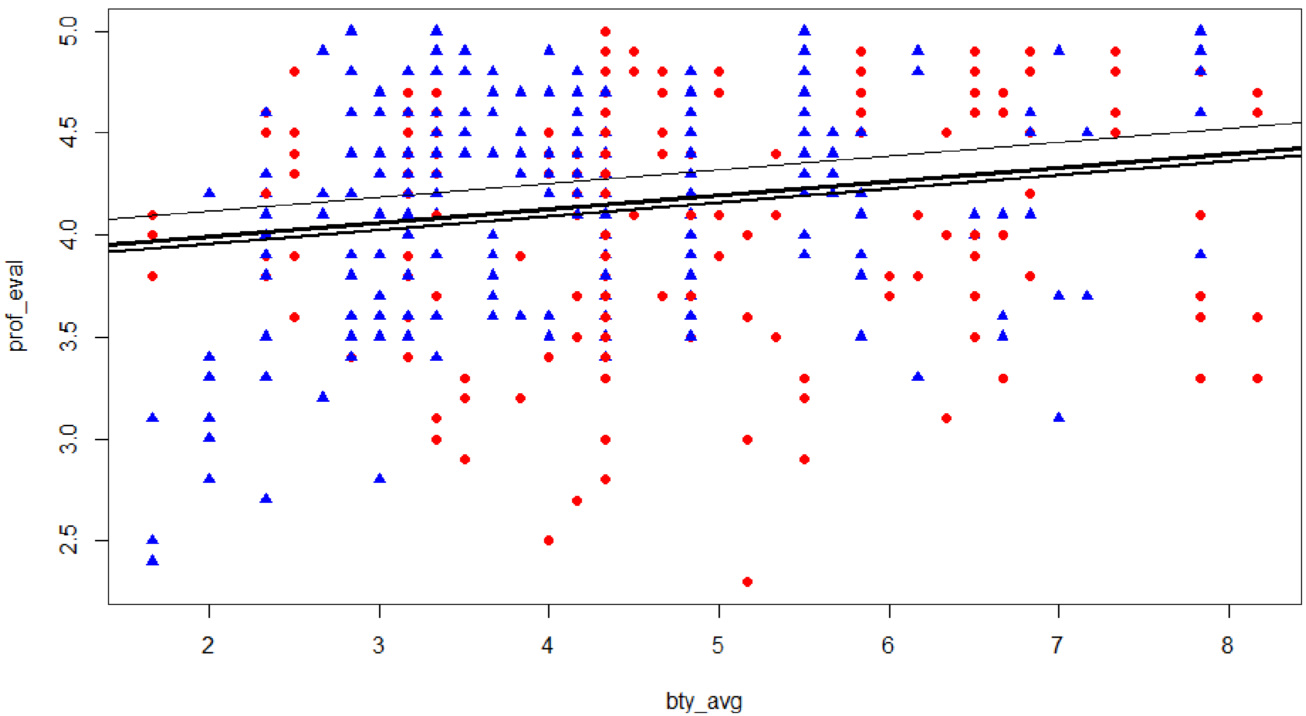
$$\underset{}{\widehat{prof\_eval}} = \underset{(.0537)}{4.2843} - \underset{(.0636)}{.1452}\ tenured - \underset{(.0748)}{.1297}\ tenure\ track$$

With a control for attractiveness (R^2 = .0465):

$$\widehat{prof\_eval} = \underset{(.0908)}{3.9816} - \underset{(.0627)}{.1262}\ tenured - \underset{(.0740)}{.1607}\ tenure\ track + \underset{(.0166)}{.0678}\ bty\_avg$$

4. Example: *'Looking Good on Course Evaluations' part 2*

Consider the effects of rank ("teaching" and "tenure track" and "tenured")
Dependent variable is average evaluation of professor (0 – 5 scale; mean = 4.175)



4. Example: *'Looking Good on Course Evaluations' part 2*

Consider the effects of rank ("teaching" and "tenure track" and "tenured")

Null hypotheses: $H_{0\text{A}} : \beta_1 = 0;$ $H_{0\text{B}} : \beta_2 = 0$

Alternative hypotheses: $H_{1\text{A}} : \beta_1 \neq 0;$ $H_{1\text{B}} : \beta_2 \neq 0$

Test statistics are $t_A = \dfrac{\widehat{\beta_1} - 0}{se(\widehat{\beta_1})};$ $t_B = \dfrac{\widehat{\beta_2} - 0}{se(\widehat{\beta_2})}$

$$\text{Estimated } \widehat{prof\_eval} = \underset{(.0908)}{3.9816} - \underset{(.0627)}{.1262}\ tenured - \underset{(.0740)}{.1607}\ tenure\ track + \underset{(.0166)}{.0678}\ bty\_avg$$

t statistics: $t_{tenured} = \dfrac{.1262}{.0627} = 2.013$ $t_{tenure\ track} = \dfrac{.1607}{.0740} = 2.172$

4. Example: *'Looking Good on Course Evaluations' part 2*

Reconsider the effects of rank ("teaching" and "tenure track" and "tenured")

Test statistic for difference between *tenured* and *tenure track*: $t = \dfrac{\widehat{\beta_1} - \widehat{\beta_2}}{se(\widehat{\beta_1} - \widehat{\beta_2})}$

Estimated $\widehat{prof\_eval}$ = 3.9816 – .1262 *tenured* – .1607 *tenure track* + .0678 *bty_avg*
(.0908) (.0627) (.0740) (.0166)

Numerator: $\widehat{\beta_1} - \widehat{\beta_2}$ = (– .1262) – (–.1607) = .0345

Denominator: $se(\hat{\beta}_1 - \hat{\beta}_2) = \sqrt{\widehat{Var}(\hat{\beta}_1 - \hat{\beta}_2)} = \sqrt{\widehat{Var}(\hat{\beta}_1) + \widehat{Var}(\hat{\beta}_2) - 2\boxed{\widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)}}$

For standard errors, need variance-covariance matrix of estimators:

	track	tenure
track	0.00547	0.00275
tenure	0.00275	0.00393

standard error equals √.0039 = .06245; *t* statistic equals ±.552; *F* statistic = .3048
Retain null hypothesis of no difference.

5A. Review of Poisson Probability Distribution

$$P(y = h) = e^{-\mu}\frac{\mu^h}{h!}, h = 0, 1, 2, \ldots$$

Flying bomb attacks during Second World War; London divided into squares, each .5 km. wide and .5 km. tall

Bombs	Observed Squares	Predicted Squares
0	229	
1	211	
2	93	
3	35	
4	7	
5	1	

Make predictions based on $\mu = 0.9288 = 535$ bombs $\div$ 576 squares

Code for frequencies: `576*dpois(c(0:5), .9288)`
Code for cumulative frequencies: `576*ppois(c(0:4), .9288, lower.tail = TRUE)`

R.D. Clark (1946) "An Application of the Poisson Process" Journal of the Institute of Actuaries 72: 481–

5B. Review of Poisson Regression

$$P(y = h) = e^{-\mu}\frac{\mu^h}{h!}, h = 0, 1, 2, \ldots$$

Model μ as: $\mu(x) = \exp(x\hat{\beta}) = e^{\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2 + \ldots}$

Combine: $P(y = h) = e^{-\exp(x\hat{\beta})}\dfrac{\exp(x\hat{\beta})^h}{h!}$

Predict: set fixed values of x_1, x_2, … , and then change them one at a time

Interpret $\hat{\beta}_j$: $100\cdot[\exp(\hat{\beta}_j\,\Delta x_j)-1]$ tells you the percent or proportional change in $\mu(x)$ from a Δx_j–unit change in x_j

5C. Review of Poisson Regression

Application: *Traffic Accidents at Intersections*

Let y_i denote the number of incidents in an intersection in a given year
Let $x_{1i} \in \{25, 30, 35, \ldots\}$ denote the average speed on nearby streets, in mph
Let $x_{2i} \in \{0, 1\}$ denote whether intersection has a traffic signal

Suppose : $\widehat{\beta_0} = 2.8, \widehat{\beta_1} = 0.012, \widehat{\beta_2} = -0.20$

Model μ as : $\mu(x) = \exp(x\hat{\beta}) = e^{\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2} = e^{2.8 + .012x_1 - .2x_2}$

Combine : $P(y = h) = e^{-\exp(x\hat{\beta})} \dfrac{\exp(x\hat{\beta})^h}{h!}$

Predict : set $x_1 = 25$, set $x_2 = 0$ and predict, then reset $x_1 = 35$ and/or reset $x_2 = 1$

R code:

```
mu.25.0 = exp(2.8 + .012*25); round(dpois(c(17:26), mu.25.0), digits = 2)

mu.25.1 = exp(2.6 + .012*25); round(dpois(c(17:26), mu.25.1), digits=2)

mu.35.0 = exp(2.8 + .012*35); round(dpois(c(17:26), mu.35.0), digits=3)

mu.35.1 = exp(2.6 + .012*35); round(dpois(c(17:26), mu.35.1), digits=3)
```

5C. Review of Poisson Regression

Application: *Traffic Accidents at Intersections*

Let y_i denote the number of incidents in an intersection in a given year
Let $x_{1i} \in \{25, 30, 35, \ldots\}$ denote the average speed on nearby streets, in mph
Let $x_{2i} \in \{0, 1\}$ denote whether intersection has a traffic signal

Suppose : $\widehat{\beta_0} = 2.8, \widehat{\beta_1} = 0.012, \widehat{\beta_2} = -0.20$

Model μ as : $\mu(x) = \exp(x\hat{\beta}) = e^{\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2} = e^{2.8 + .012x_1 - .2x_2}$

Combine : $P(y = h) = e^{-\exp(x\hat{\beta})} \dfrac{\exp(x\hat{\beta})^h}{h!}$

Predict : set $x_1 = 25$, set $x_2 = 0$ and predict, then reset $x_1 = 35$ and/or reset $x_2 = 1$

Interpret $\hat{\beta}_1$: $100 \cdot [\exp(\hat{\beta}_1 \cdot 10) - 1]$ tells you the percent or proportional change in $\mu(x)$ from increasing x_1 by 10 mph.

R code: `(mu.25.1/mu.25.0)-1; (mu.35.1/mu.35.0)-1`

Interpret $\hat{\beta}_2$: $100 \cdot [\exp(\hat{\beta}_2) - 1]$ tells you the percent or proportional change in $\mu(x)$ from adding a traffic signal.

R code: `(mu.35.0/mu.25.0)-1; (mu.35.1/mu.25.1)-1`

Readings: Wooldridge, *Introductory Econometrics 5e*, 17.3

6. Example: *Economic Model of Crime*

Dataset is crime1.RData; Wooldridge uses in examples 7.12, 8.3, 9.1, and 17.3

Population is 'young men in California born in 1960 or 1961 who have at least one arrest prior to 1986'; sample is 2,725 individuals

Dependent variable: *narr86* (number of arrests in 1986; 27.7% arrested ≥ 1x in 1986, however only 7.2% were arrested > 1x)

Explanatory variables:
pcnv (proportion of prior arrests leading to a conviction)*
avgsen (average sentence served from prior convictions, in months)*
tottime (time spent in prison since age 18 up to 1985, in months)
ptime86 (time spent in prison during 1986, in months)*
qemp86 (quarters employed during 1986, 0 – 4)
inc86 (legal income, in hundreds of $)*
black (dummy variable)
hispanic (dummy variable)
born60 (dummy variable)

* squared terms added to specification in various examples

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6. Example: *Economic Model of Crime*

Dataset is crime1.RData; Wooldridge uses in examples 7.12, 8.3, 9.1, and 17.3

TABLE 17.5 Determinants of Number of Arrests for Young Men

Dependent Variable: *narr86*		
Independent Variables	Linear (OLS)	Exponential (Poisson QMLE)
pcnv	−.132 (.040)	−.402 (.085)
avgsen	−.011 (.012)	−.024 (.020)
tottime	.012 (.009)	.024 (.015)
ptime86	−.041 (.009)	−.099 (.021)
qemp86	−.051 (.014)	−.038 (.029)
inc86	−.0015 (.0003)	−.0081 (.0010)
black	.327 (.045)	.661 (.074)
hispan	.194 (.040)	.500 (.074)
born60	−.022 (.033)	−.051 (.064)
constant	.577 (.038)	−.600 (.067)

6. Example: *Economic Model of Crime*

see R script: Lecture 23B crime.R

Example:
```
load("C:/crime1.RData"); attach(data)
pois.D <- glm(narr86 ~ pcnv + ptime86 + qemp86 + black + hispan, poisson)
reg.D <- lm(narr86 ~ pcnv + ptime86 + qemp86 + black + hispan)
```

Compare:
```
stargazer(reg.D, pois.D, type="text", single.row=FALSE, omit.stat=c("f", "ser"))
```

Interpret: for each quarter that man is employed, arrests decrease by 20% *proportionately*
black men are arrested 103% more often than white men
hispanic men are arrested 70% more often than white men

6. Example: *Economic Model of Crime*

Recall from earlier : $P(y = h) = e^{-\exp(x\hat{\beta})} \dfrac{\exp(x\hat{\beta})^h}{h!}$

where : $\exp(x\hat{\beta}) = e^{\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2 + \ldots}$

Use $\widehat{\beta_0} = -.578$, $\hat{\beta}_{pcnv} = -.379$, $\hat{\beta}_{ptime86} = -.096$, $\hat{\beta}_{qemp86} = -.226$, $\hat{\beta}_{black} = .710$, $\hat{\beta}_{hispan} = .533$

Suppose a male has no convictions (*pcnv* = 0), spent no time in prison in 1986 (*ptime86* = 0), and was employed for 2 quarters in 1986 (*qemp86* = 2).

If that man is white (*black* = 0, *hispan* = 0), then:	$x\beta = -1.030$;	$\exp(x\beta) = .357$
If that man is black (*black* = 1, *hispan* = 0), then:	$x\beta = -0.320$;	$\exp(x\beta) = .726$
If that man is hispanic (*black* = 0, *hispan* = 1), then:	$x\beta = -0.498$;	$\exp(x\beta) = .608$

Probabilities of no arrests (h = 0):	white:	70.0 %
	black:	48.4 %
	hispanic:	54.4 %

Probabilities of one arrest (h = 1):	white:	25.0 %
	black:	35.1 %
	hispanic:	33.1 %

Readings: Wooldridge, *Introductory Econometrics 5e*, 17.3

6. Example: *Economic Model of Crime*

see R script: Lecture 23B crime.R

Example:

```
load("C:/crime1.RData"); attach(data)
pois.D <- glm(narr86 ~ pcnv + inc86 + black + hispan, poisson)
```

Dependent variable *(narr86)* is number of arrests in 1986

Model with controls for prior convictions and for income in 1986 (R^2 = .069):

$$\widehat{narr86} = \underset{(.057)}{-.676} \; - \underset{(.085)}{.433}\, pcnv \; - \underset{(.001)}{.009}\, inc86 \; + \underset{(.074)}{.471}\, hispan \; + \underset{(.073)}{.644}\, black$$

A one-unit ($100) increase in *inc86* changes expected number of arrests by –0.9%

Interpret $\hat{\beta}_{inc86}$: $100\cdot[\exp(\hat{\beta}_{inc86}\cdot 1)-1]$ tells you the percent or proportional change in $\mu(x)$ from increasing *inc86* by $100

Readings: Wooldridge, *Introductory Econometrics 5e*, 17.3

6. Example: *Economic Model of Crime*

see R script: Lecture 23B crime.R

Example:
```
load("C:/crime1.RData"); attach(data)
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Model with controls for prior convictions and for income in 1986 (R^2 = .069):

$$\widehat{narr86} = \underset{(.057)}{-.676} \; \underset{(.085)}{-\, .433}\, pcnv \; \underset{(.001)}{-\, .009}\, inc86 \; \underset{(.074)}{+\, .471}\, hispan \; \underset{(.073)}{+\, .644}\, black$$

A one-unit 'increase' in *hispan* changes expected number of arrests by +60%

Interpret $\hat{\beta}_{hispan}$: $100 \cdot [\exp(\hat{\beta}_{hispan} \cdot 1) - 1]$ tells you the percent or proportional change in $\mu(x)$ from changing *hispan* from 0 to 1

6. Example: *Economic Model of Crime*

see R script: Lecture 23B crime.R

Example:

```
load("C:/crime1.RData"); attach(data)
pois.D <- glm(narr86 ~ pcnv + inc86 + black + hispan, poisson)
```

Dependent variable *(narr86)* is number of arrests in 1986

Model with controls for prior convictions and for income in 1986 (R^2 = .069):

$$\widehat{narr86} = \underset{(.057)}{-.676} - \underset{(.085)}{.433}\, pcnv - \underset{(.001)}{.009}\, inc86 + \underset{(.074)}{.471}\, hispan + \underset{(.073)}{.644}\, black$$

A one-unit 'increase' in *black* changes expected number of arrests by +90%

Interpret $\hat{\beta}_{black}$: $100 \cdot [\exp(\hat{\beta}_{black} \cdot 1) - 1]$ tells you the percent or proportional change in $\mu(x)$ from changing *black* from 0 to 1

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Readings: Wooldridge, *Introductory Econometrics 5e*, 17.3

6. Example: *Economic Model of Crime*

Recall from earlier : $P(y = h) = e^{-\exp(x\hat{\beta})} \dfrac{\exp(x\hat{\beta})^h}{h!}$

where : $\exp(x\hat{\beta}) = e^{\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2 + \ldots}$

Use $\widehat{\beta_0} = -.676$, $\hat{\beta}_{pcnv} = -.433$, $\hat{\beta}_{inc86} = -.009$, $\boxed{\hat{\beta}_{hispan} = .471\ , \hat{\beta}_{black} = .644}$

Suppose a man has no convictions ($pcnv = 0$) and earned \$5,500 income in 1986 ($inc86 = 55$)

				Probabilities of:	
r/e:	$x\beta$	$\exp(x\beta)$	no arrests (h = 0):	one arrest (h = 1):	two arrests (h = 2)
white	–1.152	= .316	72.9 %	23.0 %	3.6 %
Hispanic	–0.681	= .506	60.3 %	30.5 %	7.7 %
black	–0.508	= .602	54.8 %	33.0%	9.9 %

6. Example: *Economic Model of Crime*

Consider the effects of race/ethnicity (white vs. Hispanic, white vs. black)

Dependent variable *(narr86)* is number of arrests in 1986

Model with controls for prior convictions and for income in 1986 (R^2 = .069):

$$\widehat{narr86} = -.676 - .433\, pcnv - .009\, inc86 + .471\, hispan + .644\, black$$

Std. errors:	(.057)	(.085)	(.001)	(.074)	(.073)
Robust std. errors:	(.074)	(.103)	(.001)	(.094)	(.099)

Initial tests of hypothesis:

$$\mathrm{H}_{0h} : \hat{\beta}_{hispan} = 0 \qquad z = \frac{.471}{.074} = 6.403 > 1.96 \qquad z = \frac{.471}{.094} = 5.041 > 1.96$$

$$\mathrm{H}_{0b} : \hat{\beta}_{black} = 0 \qquad z = \frac{.644}{.073} = 8.777 > 1.96 \qquad z = \frac{.644}{.099} = 6.499 > 1.96$$

POLS 6481. Research Design and Quantitative Methods II
Lecture 23. Binary Independent Variables I: Different Intercepts for Different Groups
Readings: Wooldridge, *Introductory Econometrics 5e*, 17.3

6. Example: *Economic Model of Crime*

Consider the effects of race/ethnicity (Hispanic vs. black)

The null hypothesis is: $H_0 : \beta_1 = \beta_2$

The test statistic is: $z = \frac{\widehat{\beta_1} - \widehat{\beta_2}}{se\left(\widehat{\beta_1} - \widehat{\beta_2}\right)} = \frac{difference\ of\ coefficients}{standard\ error\ of\ difference\ of\ coefficients}$

where $se(\hat{\beta}_1 - \hat{\beta}_2) = \sqrt{\widehat{Var}(\hat{\beta}_1 - \hat{\beta}_2)} = \sqrt{\widehat{Var}(\hat{\beta}_1) + \widehat{Var}(\hat{\beta}_2) - 2\widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)}$

Numerator: $\hat{\beta}_{black} - \hat{\beta}_{hispanic} = .644 - .471 = .173$

For standard error, we need variance-covariance matrix of estimators:

	black	hispanic
black	0.005383	0.001989
hispanic	0.001989	0.005422

Denominator: $\sqrt{.005383 + .005422 - 2 \cdot .001989} = \sqrt{.006828} = .0826$

z statistic equals 2.087 > 1.96

6. Example: *Economic Model of Crime*

Consider the effects of race/ethnicity (Hispanic vs. black)

The null hypothesis is: $H_0 : \beta_1 = \beta_2$

The test statistic is: $z = \frac{\widehat{\beta_1} - \widehat{\beta_2}}{se\left(\widehat{\beta_1} - \widehat{\beta_2}\right)} = \frac{difference\ of\ coefficients}{standard\ error\ of\ difference\ of\ coefficients}$

where $se(\hat{\beta}_1 - \hat{\beta}_2) = \sqrt{\widehat{Var}(\hat{\beta}_1 - \hat{\beta}_2)} = \sqrt{\widehat{Var}(\hat{\beta}_1) + \widehat{Var}(\hat{\beta}_2) - 2\widehat{Cov}(\hat{\beta}_1, \hat{\beta}_2)}$

Numerator: $\hat{\beta}_{black} - \hat{\beta}_{hispanic} = .644 - .471 = .173$

For robust standard errors, we need new variance-covariance matrix of estimators:

	black	hispanic
black	0.009816	0.003243
hispanic	0.003243	0.008746

Denominator: $\sqrt{.009816 + .008746 - 2 \cdot .003243} = \sqrt{.006828} = .1099$

z statistic equals 1.5695 < 1.96