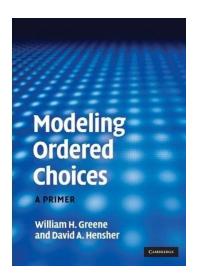
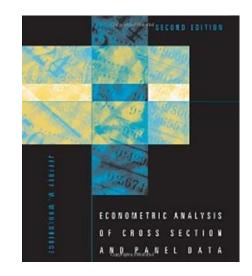
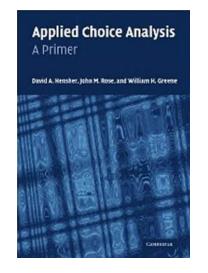


#### 1. Descriptive Tools, Regression, Panel Data

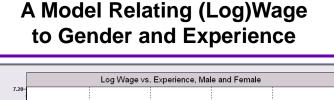


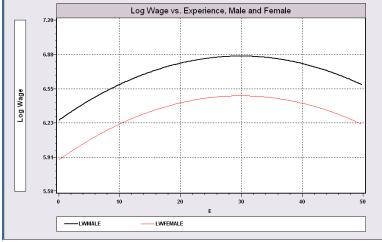




## **Model Building in Econometrics**

- Parameterizing the model
  - Nonparametric analysis
  - Semiparametric analysis
  - Parametric analysis
- Sharpness of inferences follows from the strength of the assumptions





#### **Cornwell and Rupert Panel Data**

#### Cornwell and Rupert Returns to Schooling Data, 595 Individuals, 7 Years Variables in the file are

EXP	= work experience
WKS	= weeks worked
000	<ul> <li>accupation, 1 if blue collar,</li> </ul>
IND	= 1 if manufacturing industry
SOUTH	= 1 if resides in south
SMSA	= 1 if resides in a city (SMSA)
MS	= 1 if married
FEM	= 1 if female
UNION	<u>= 1 if wage set by union contract</u>
ED	= years of education
LWAGE	= log of wage = dependent variable in regressions

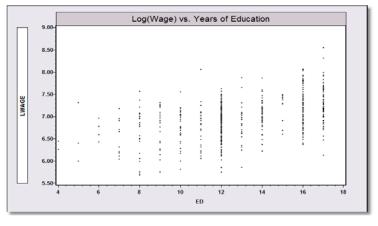
These data were analyzed in Cornwell, C. and Rupert, P., "Efficient Estimation with Panel Data: An Empirical Comparison of Instrumental Variable Estimators," Journal of Applied Econometrics, 3, 1988, pp. 149-155.



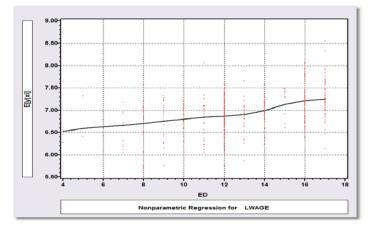
🎟 Data Ed	itor								
28/900 Vars;	28/900 Vars; 11111 Rows: 4165 Ob: Cell: 0								
	LOGWAGE	EDUC							
1 »	5.56068	9							
2 »	5.72031	9							
3 »	5.99645	9							
4 »	5.99645	9							
5 »	6.06146	9							
6 »	6.17379	9							
7 »	6.24417	9							
8 »	6.16331	11							
9 »	6.21461	11							
10 »	6.2634	11							
11 »	6.54391	11							
12 »	6.69703	11							
13 »	6.79122	11							
14 »	6.81564	11							
15 »	5.65249	12							
16 »	6.43615	12							
17 »	6.54822	12							
18 »	6.60259	12							
19 »	6.6958	12							
20 »	6.77878	12							
21 »	6.86066	12							
20	C 15C00	10							



#### **Application**: Is there a relationship between Log(wage) and Education?

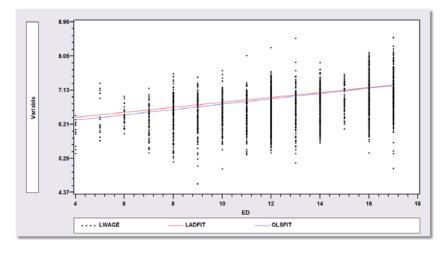


#### Nonparametric Regression Kernel regression of y on x



#### **Semiparametric Regression**: Least absolute deviations regression of y on x

#### Parametric Regression: Least squares – maximum likelihood – regression of y on x





## A First Look at the Data Descriptive Statistics

- Basic Measures of Location and Dispersion
- Graphical Devices
  - Box Plots
  - Histogram
  - Kernel Density Estimator



Descriptive	Statistics	for	11	variables	
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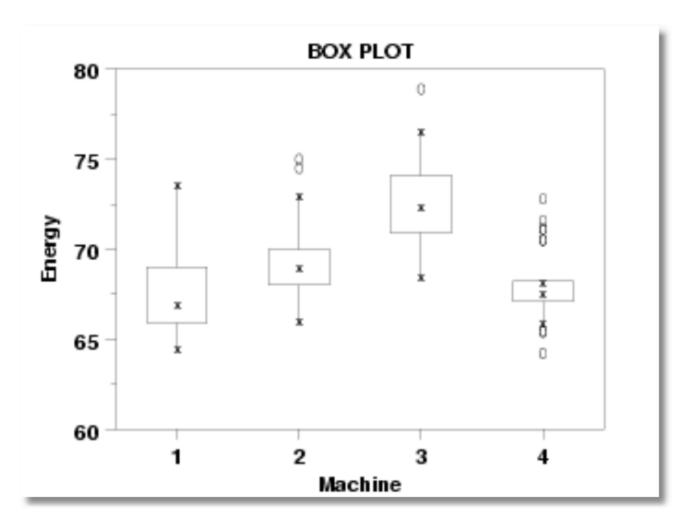
issing	Cases	Maximum	Minimum	Std.Dev.	Mean	Variable
0	4165	51.0	1.0	10.96637	19.85378	EXP
0	4165	52.0	5.0	5.129098	46.81152	WKS
0	4165	1.0	0.0	. 499935	.511164	0000
0	4165	1.0	0.0	. 489003	.395438	IND
0	4165	1.0	0.0	. 453944	.290276	SOUTHİ
0	4165	1.0	0.0	.475821	.653782	SMSA
0	4165	1.0	0.0	.388826	.814406	MS
Ō	4165	1.0	0.0	.316147	112605	FEM
õ	4165	1.0	0.0	491202	363986	UNION
ŏ	4165	8.537000	4.605170	.461512	6.676346	LWAGE
- 0	4165	7.0	1.0	2.000240	4.0	YEAR

Subsample			Mean	Std.Dev.	Cases	Sum of wts	Missing
YEAR		1	6.375173	. 388426	595	595.00	 (
YEAR	=	2	6.465212	362702	595	595.00	
YEAR	=	3	6.596717	.446691	595	595.00	
YEAR	=	4	6.696079	.440750	595	595.00	
ZEAR	=	5	6.786454	.424013	595	595.00	
ZEAR	=	6	6.864045	.424021	595	595.00	
ZEAR	=	7	6.950745	. 438403	595	595.00	
Full Sampl	le		6.676346	.461512	4165	4165.00	

l



#### **Box Plots**





#### From Jones and Schurer (2011)

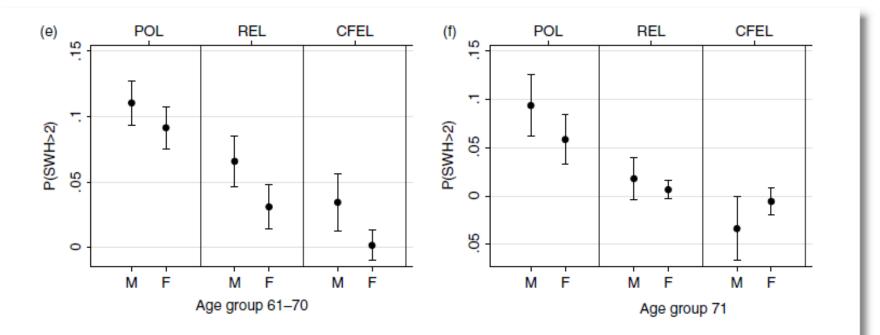
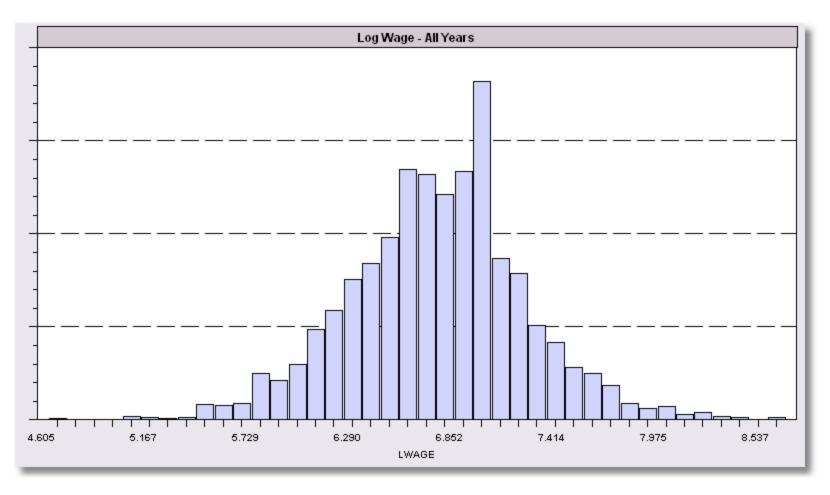


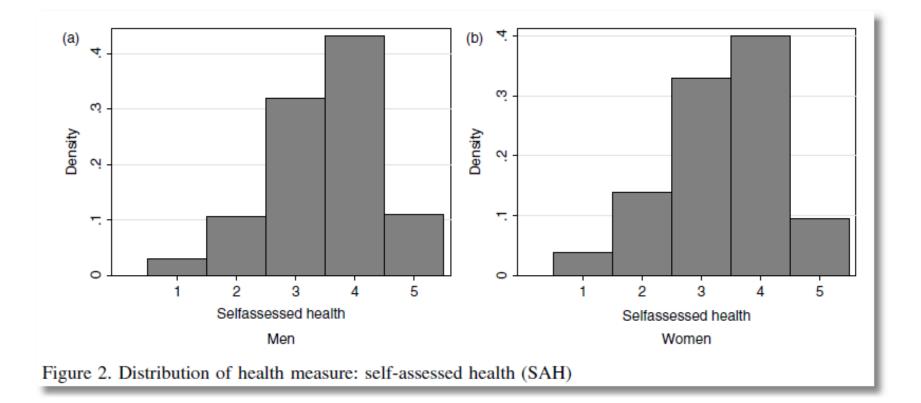
Figure 4. Marginal effects of income on the probability to report satisfaction with health greater than two for both men (M) and women (W) obtained from three different models: pooled ordered logit (POL), random-effects logit (REL), and conditional fixed-effects logit (CFEL)



#### **Histogram for LWAGE**



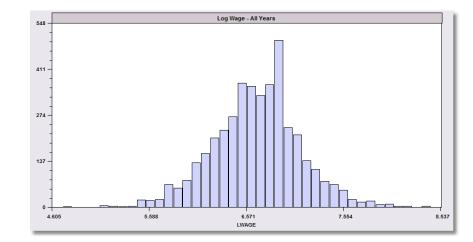




[Topic 1-Regression] 11/37

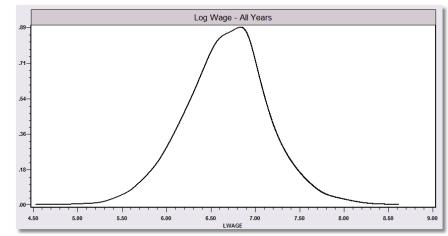


#### The kernel density estimator is a histogram (of sorts).



$$\hat{f}(x_{m}^{*}) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{B} K \left[ \frac{x_{i} - x_{m}^{*}}{B} \right], \text{ for a set of points } x_{m}^{*}$$

- B = "bandwidth" chosen by the analyst
- K = the kernel function, such as the normal or logistic pdf (or one of several others)
- $x^*$  = the point at which the density is approximated. This is essentially a histogram with small bins.





#### **Kernel Density Estimator**

The curse of dimensionality

$$\hat{f}(x_{m}^{*}) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{B} K\left[\frac{x_{i} - x_{m}^{*}}{B}\right], \text{ for a set of points } x_{m}^{*}$$

B = "bandwidth"

K = the kernel function

 $x^* =$  the point at which the density is approximated.

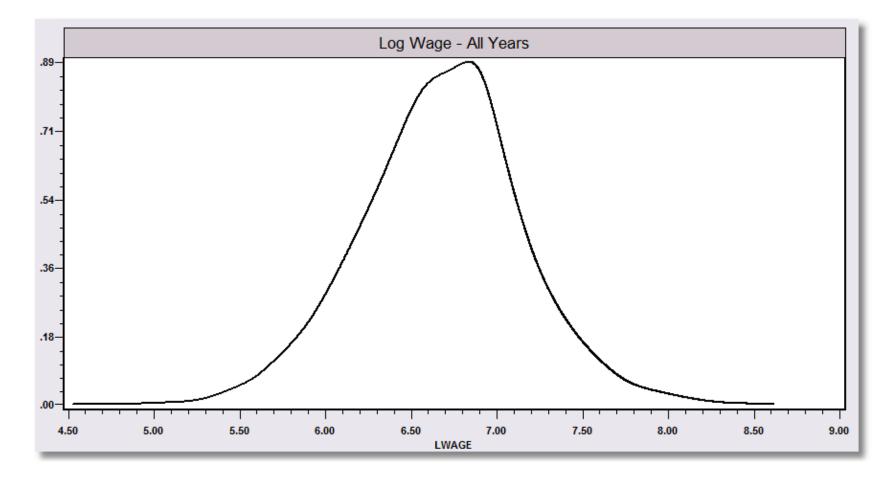
$$\hat{f}(x^*)$$
 is an estimator of  $f(x^*)$ 

$$\frac{1}{n}\sum_{i=1}^{n}Q(x_{i}\mid x^{*})=\overline{Q}(x^{*}).$$

But,  $Var[\overline{Q}(x^*)] \neq \frac{1}{N} \times Something$ . Rather,  $Var[\overline{Q}(x^*)] = \frac{1}{N^{3/5}} * Something$ l.e.,  $\hat{f}(x^*)$  does not converge to  $f(x^*)$  at the same rate as a mean converges to a population mean.



#### **Kernel Estimator for LWAGE**





#### From Jones and Schurer (2011)

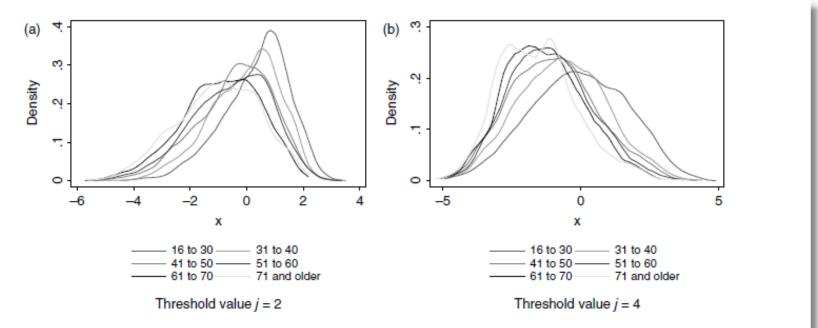


Figure 7. Probability distribution of individual fixed effect obtained from the conditional fixed-effects logit (CFEL), when the threshold values are j = 2 and j = 4 for the sample of men

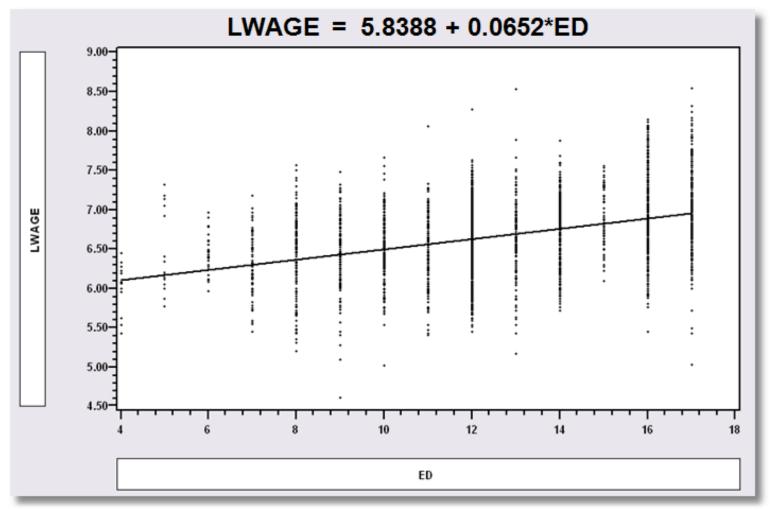


## Objective: Impact of Education on (log) Wage

- **Specification**: What is the right model to use to analyze this association?
- Estimation
- Inference
- Analysis



#### **Simple Linear Regression**





#### **Multiple Regression**

Ordinary LHS=LWAGE Regression Residual Total Fit Model test	least squares Mean Standard devia No. of observa Sum of Squares Sum of Squares Sum of Squares Standard erros R-squared F[ 9, 4155]	ation = ations = s = s = s =	6. - 34 54 88	67635 46151 4165 5.763 1.142 6.905 36089 38985 98231	DegFreedom 9 4155 4164 Root MSE R-bar squared Prob F > F*	Mean square 38.41812 .13024 .21299 .36045 1 .38853 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z∮		nfidence erval
Constant ED EXP WKS OCC SOUTH SMSA MS FEM UNION	5.44028*** .05682*** .01040*** .00525*** 14867*** 07024*** .13241*** .08568*** 37561*** .09995***	.07208 .00267 .00054 .00111 .01507 .01279 .01235 .02108 .02577 .01318	75.48 21.25 19.37 4.71 -9.87 -5.49 10.72 <u>4.06</u> -14.58 7.58	.0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000	5.29902 .05158 .00935 .00306 17819 09530 .10820 .04435 42611 .07411	5.58155 .06207 .01145 .00743 11914 04517 .15663 <u>.12700</u> 32511 .12579



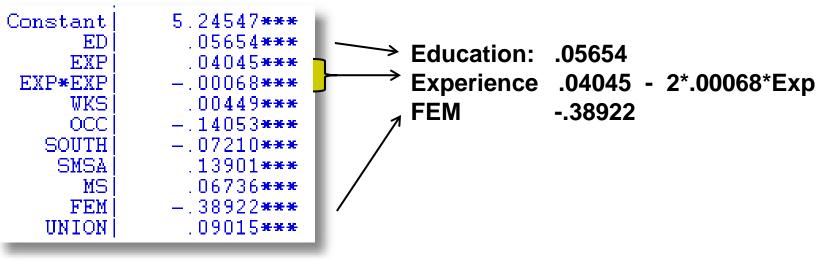
#### **Specification: Quadratic Effect of Experience**

Ordinary LHS=LWAGE Regressic Residual Total Fit Model tes	Standard dev No. of obser on Sum of Squar Sum of Squar Standard err R-squared	iation = vations = es = es = or of e = =	6. 37 51 88	67635 46151 4165 0.955 5.950 6.905 35243 41826 66153	DegFreedom 10 4154 4164 Root MSE R-bar squares Prob F > F*	Mean square 37.09546 .12421 .21299 .35196 d .41686 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z		nfidence erval
Constant ED	5.24547 <b>***</b> 05654 <b>***</b>	.07170	73.15 21.64	. 0000		5.38600
EXP EXP <b>*</b> EXP	.04045 <b>***</b> 00068 <b>***</b>	.00217 .4783D-04	18.61 -14.24	.0000	.03619 00077	.04471 00059
WKS OCC SOUTH SMSA	.00449*** 14053*** 07210*** .13901***	.00109 .01472 .01249 .01207	4.12 -9.54 -5.77 11.51	.0000 .0000 .0000 .0000	16939	.00662 11167 04762 .16267
MS FEM	.06736 <b>***</b> 38922 <b>***</b>	.02063 .02518	3.26 -15.46	.0011	43857	.10779 33987
	.09015*** xx or D+xx => mul * ==> Significa				.06488	. 11542

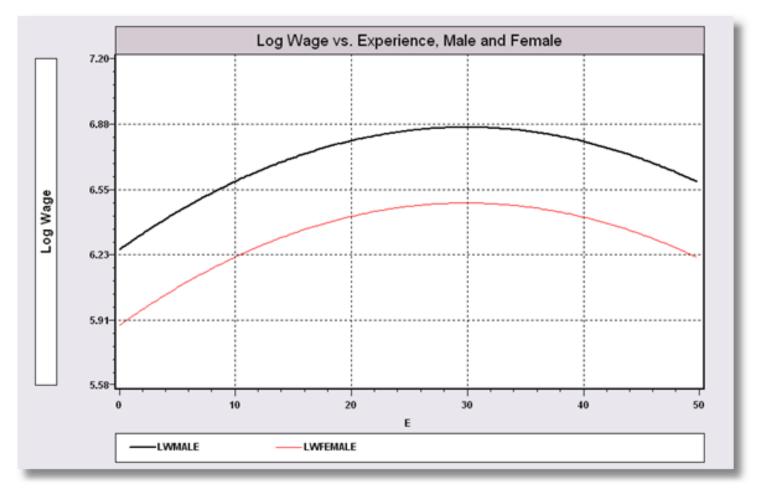


#### **Partial Effects**

Ordinary	least squares regres	sion			
LHS=LWAGE	Mean	=	6.67635		
	Standard deviation	=	. 46151		
	No. of observations	=	4165	DegFreedom	Mean square
Regression	Sum of Squares	=	378.218	11	34.38347
Residual	Sum of Squares	=	508.687	4153	.12249
Total	Sum of Squares	=	886.905	4164	. 21299
	Standard error of e	=	. 34998	Root MSE	. 34948
Fit	R-squared	=	. 42645	R-bar squared	
Model test	F[ 11, 4153]	=	280.71214	Prob $F > F*$	.00000



#### Model Implication: Effect of Experience and Male vs. Female





## **Hypothesis Test About Coefficients**

- Hypothesis
  - Null: Restriction on  $\boldsymbol{\beta}$ :  $\boldsymbol{R}\boldsymbol{\beta} \boldsymbol{q} = \boldsymbol{0}$
  - Alternative: Not the null
- Approaches
  - Fitting Criterion: R<sup>2</sup> decrease under the null?
  - Wald: **Rb q** close to **0** under the alternative?



#### **Hypotheses**

Ordinary LHS=LWAGE Regressio Residual Total Fit Model tes	Standard dev: No. of observent Sum of Square Sum of Square Sum of Square R-squared	= iation = vations = es = es = or of e = =	6. 37 51 88	$ \begin{array}{r}     67635 \\     46151 \\     4165 \\     0.955 \\     5.950 \\     6.905 \\     35243 \\     41826 \\     66153 \\   \end{array} $	DegFreedom 10 4154 4164 Root MSE R-bar squared Prob F > F*	Mean square 37.09546 .12421 .21299 .35196 d .41686 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z≉		nfidence erval
Constant ED EXP EXP*EXP WKS OCC SOUTH SMSA MS FEM UNION	5.24547*** .05654*** .04045*** 00068*** .00449*** 14053*** 07210*** .13901*** .06736*** 38922*** .09015***	.07170 .00261 .00217 .4783D-04 .00109 .01472 .01249 .01207 .02063 .02518 .01289	$\begin{array}{r} 73.15\\ 21.64\\ 18.61\\ -14.24\\ 4.12\\ -9.54\\ -5.77\\ 11.51\\ 3.26\\ -15.46\\ 6.99\end{array}$	.0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0011 .0000 .0000	5.10493 .05142 .03619 00077 .00235 16939 09658 .11534 .02692 43857 .06488	5.38600 .06166 .04471 00059 .00662 11167 04762 .16267 .10779 33987 .11542

\*\*\*, \*\*, \* ==> Significance at 1%, 5%, 10% level.

All Coefficients = 0? R = [ 0 | 1 ] q = [0]

ED Coefficient = 0?
R = 0,1,0,0,0,0,0,0,0,0,0
$\mathbf{q} = 0$



## **Hypothesis Test Statistics**

Subscript 0 = the model under the null hypothesis

Subscript 1 = the model under the alternative hypothesis

1. Based on the Fitting Criterion  $R^2$ 

$$F = \frac{(R_1^2 - R_0^2) / J}{(1 - R_1^2) / (N - K_1)} = F[J, N - K_1]$$

2. Based on the Wald Distance : Note, for linear models, W = JF.

Chi Squared = 
$$(\mathbf{Rb} - \mathbf{q})' \Big[ \mathbf{R} \Big( s^2 (\mathbf{X}'_1 \mathbf{X}_1)^{-1} \Big) \mathbf{R}' \Big]^{-1} (\mathbf{Rb} - \mathbf{q})$$

#### Hypothesis: All Coefficients Equal Zero

Ordinary LHS=LWAGE Regression Residual Total Fit Model tes	Sum of Square Sum of Square - Standard erro R-squared	= ation = ations = s = s = r of e = =	6. 37 51 88	67635 46151 4165 0.955 5.950 6.905 35243 41826 66153	DegFreedom 10 4154 4164 Root MSE R-bar square Prob F > F*	Mean square 37.09546 .12421 .21299 .35196 1 .41686 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z		nfidence erval
Constant ED EXP EXP*EXP WKS OCC SOUTH SMSA MS FEM UNION	5.24547*** .05654*** .04045*** 00068*** 14053*** 14053*** .07210*** .13901*** .06736*** 38922*** .09015***	.07170 .00261 .00217 .4783D-04 .00109 .01472 .01249 .01207 .02063 .02518 .01289	73.15 21.64 18.61 -14.24 4.12 -9.54 -5.77 11.51 3.26 -15.46 6.99	.0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0011 .0000 .0000	5.10493 .05142 .03619 00077 .00235 16939 09658 .11534 .02692 43857 .06488	5.38600 .06166 .04471 00059 .00662 11167 04762 .16267 .10779 33987 .11542

nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx. \*\*\*, \*\*, \* ==> Significance at 1%, 5%, 10% level. All Coefficients = 0? R = [0 | I] q = [0] $R_1^2 = .41826$  $R_0^2 = .00000$ = 298.7 with [10,4154] F Wald =  $b_{2-11}[V_{2-11}]^{-1}b_{2-11}$ = 2988.3355Note that Wald = JF = 10(298.7)(some rounding error)

#### Hypothesis: Education Effect = 0

Ordinary LHS=LWAGE Regression Residual Total Fit Model test	Sum of Square Sum of Square Standard erro R-squared	ation = vations = es = es = or of e = =	6. 37 51 88		DegFreedom 10 4154 4164 Root MSE R-bar squared Prob F > F*	Mean square 37.09546 .12421 .21299 .35196 1 .41686 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z*		nfidence erval
Constant	5.24547***	.07170	73.15	.0000	5.10493	5.38600
ED	.05654***	.00261	21.64	.0000	.05142	.06166
EXP*EXP WKS OCC SOUTH SMSA MS FEM UNION	.04045*** 00068*** .00449*** 14053*** 07210*** .13901*** .06736*** 38922*** .09015***	.00217 .4783D-04 .00109 .01472 .01249 .01207 .02063 .02518 .01289	$ \begin{array}{r} 18.61 \\ -14.24 \\ 4.12 \\ -9.54 \\ -5.77 \\ 11.51 \\ 3.26 \\ -15.46 \\ 6.99 \\ \end{array} $	.0000 .0000 .0000 .0000 .0000 .0000 .0011 .0000 .0000	00077 .00235 16939 09658 .11534 .02692 43857 .06488	.04471 00059 .00662 11167 04762 .16267 .10779 33987 .11542

\*\*\*, \*\*, \* ==> Significance at 1%, 5%, 10% level.

ED Coefficient = 0?  $\mathsf{R} = 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0$ q = 0 $R_1^2 = .41826$  $R_0^2 = .35265$  (not shown) F = 468.29Wald =  $(.05654-0)^2/(.00261)^2$ = 468.29Note  $F = t^2$  and Wald = F For a single hypothesis about 1 coefficient.

## **Hypothesis: Experience Effect = 0**

Ordinary LHS=LWAGE Regression Residual Total Fit Model test	Sum of Square Sum of Square - Standard erro R-squared	ation = ations = s = s = s =	6. - 37 51 88	$ \begin{array}{c}     67635 \\     46151 \\     4165 \\     0.955 \\     5.950 \\     6.905 \\     35243 \\     41826 \\     66153 \\   \end{array} $	DegFreedom 10 4154 4164 Root MSE R-bar squared Prob F > F*	Mean square 37.09546 .12421 .21299 .35196 1 .41686 .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z		nfidence erval
Constant	5.24547 <b>***</b> 05654 <b>***</b>	.07170	73.15	. 0000	5.10493	5.38600
EXP EXP*EXP	.04045 <b>***</b> 00068 <b>***</b>	.00217 .4783D-04	18.61	.0000	.03619 00077	.04471
WKS OCC SOUTH SMSA MS FEM UNION	.00449*** 14053*** .13901*** .06736*** 38922*** .09015***	.00109 .01472 .01249 .01207 .02063 .02518 .01289	4.12 -9.54 -5.77 11.51 3.26 -15.46 6.99	.0000 .0000 .0000 .0000 .0011 .0000 .0000	.00235 16939 09658 .11534 .02692 43857 .06488	.00662 11167 04762 .16267 .10779 33987 .11542

\*\*\*, \*\*, \* ==> Significance at 1%, 5%, 10% level.

No	Experience effect?
R =	0,0,1,0,0,0,0,0,0,0,0 0,0,0,1,0,0,0,0,0,
q =	0 0
R <sub>0</sub> <sup>2</sup>	= .33475, R <sub>1</sub> <sup>2</sup> = .41826 = 298.15
Wal	d = 596.3 (W* = 5.99)

	1	2	3	4	
1	0.0050797	-0.000108601	-3.80795e-005	6.45458e-007	-5.
2	-0.000108601	6.74903e-006	2.7876e-007	9.39971e-010	1.
3	-3.80795e-005	2.7876e-007	4.66184e-006	-9.95114e-008	-В.
4	6.45458e-007	9.39971e-010	-9.95114e-008	2.25567e-009	2.
5	-5.61401e-005	1.23728e-007	-8.17968e-008	2.51799e-009	1.
6	-0.000369037	2.09061e-005	1.68653e-006	-2.68766e-008	-5.
7	-0.000120975	4.14423e-006	2.20649e-007	6.31692e-009	-3.
8	-2.8469e-005	-3.35864e-006	3.55984e-007	-2.17099e-008	-7.
9	-0.000297658	-1.56903e-006	-4.25998e-006	6.04884e-008	-3.



#### **Built In Test**

Ordinary LHS=LWAGE Regression Residual Total Fit Model test Wald Test: F Test:	least square Mean Standard dev No. of obser Sum of Squar Sum of Squar Sum of Squar Standard err R-squared F[ 10, 4154 Chi-squared F ratio[ 2,	iation = vations = es = es = or of e = ] = [ 2] =	6. 37 51 88	67635 46151 4165 0.955 5.950 6.905 35243 41826 <del>66153</del> 6.303 8.152	DegFreedom 10 4154 4164 Root MSE R-bar square Prob F > F* Prob C2 > C2 Prob F > F*	.00000 • = .00000
LWAGE	Coefficient	Standard Error	z	Prob  z >Z		nfidence erval
Constant ED EXP EXP*EXP WKS OCC SOUTH SMSA MS FEM UNION	5.24547*** .05654*** .04045*** 00068*** .00449*** 14053*** 07210*** .13901*** .06736*** 38922*** .09015***	.07170 .00261 .00217 .4783D-04 .00109 .01472 .01249 .01207 .02063 .02518 .01289	73.15 21.64 18.61 -14.24 4.12 -9.54 -5.77 11.51 3.26 -15.46 6.99	.0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0011 .0000 .0000	5.10493 .05142 .03619 00077 .00235 16939 09658 .11534 .02692 43857 .06488	5.38600 .06166 .04471 00059 .00662 11167 04762 .16267 .10779 33987 .11542

#### **Robust Covariance Matrix**

The White Estimator

Est.Var[**b**] = 
$$(\mathbf{X}'\mathbf{X})^{-1} \left[\sum_{i} e_{i}^{2} \mathbf{x}_{i} \mathbf{x}_{i}'\right] (\mathbf{X}'\mathbf{X})^{-1}$$

- What does robustness mean?
- Robust to: Heteroscedasticty
- Not robust to:
  - Autocorrelation
  - Individual heterogeneity
  - The wrong model specification
- 'Robust inference'

#### **Robust Covariance Matrix**

	Standard dev Number of ob Parameters Degrees of f Sum of squar Standard err R-squared Adjusted R-s	iation = servs. = reedom = es = or of e = quared = ] (prob) = robust cova:	6. 	trix.			Uncor	rected
LWAGE	Coefficient	Standard Error	z	Prob.  z >Z <b>*</b>		nfidence erval	- Standard Error	z
	5.24547*** .05654*** .04045*** 00068*** .00449*** 14053*** 07210*** .13901*** .06736*** 38922*** .09015*** x or D+xx => mul * ==> Significa	tiply by 10		.0000 .0013 .0000 .0000 <b>r +xx</b> .	5.09715 .05119 .03616 00078 .00220 17009 09707 .11550 .02622 43617 .06572	5.39379 .06189 .04474 00059 .00677 11098 04714 .16252 .10849 34227 .11458	.07170 .00261 .00217 .4783D-04 .00109 .01472 .01249 .01207 .02063 .02518 .01289	$\begin{array}{r} 73.15\\ 21.64\\ 18.61\\ -14.24\\ 4.12\\ -9.54\\ -5.77\\ 11.51\\ 3.26\\ -15.46\\ 6.99\end{array}$



# Bootstrapping

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## **Estimating the Asymptotic Variance of an Estimator**

- Known form of asymptotic variance: Compute from known results
- Unknown form, known generalities about properties: Use bootstrapping
  - Root N consistency
  - Sampling conditions amenable to central limit theorems
  - Compute by resampling mechanism within the sample.



## Bootstrapping

#### Method:

- 1. Estimate parameters using full sample:  $\rightarrow$  **b**
- 2. Repeat R times:

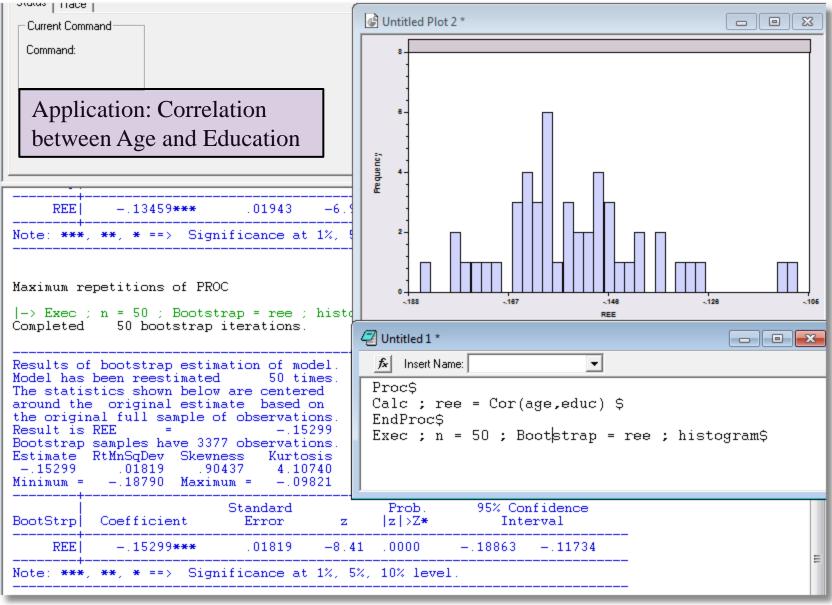
Draw n observations from the n, with replacement Estimate  $\beta$  with **b**(r).

3. Estimate variance with

 $V = (1/R)\Sigma_r [b(r) - b][b(r) - b]'$ 

(Some use mean of replications instead of **b**. Advocated (without motivation) by original designers of the method.)







#### **Bootstrap Regression - Replications**

```
namelist;x=one,y,pg$
regress;lhs=g;rhs=x$
proc
regress;quietly;lhs=g;rhs=x$
endproc
execute;n=20;bootstrap=b$
matrix;list;bootstrp $
```

Define X Compute and display b Define procedure ... Regression (silent) Ends procedure 20 bootstrap reps Display replications

#### **Results of Bootstrap Procedure**

Variable   Coeff	icient S	tandard Err	or t-ratio	P[ T >t]	Mean of X
	03692***	.00132	-9.196 28.022 -8.042	.0000	9232.86 2.31661
Completed 20	bootstrap	iterations.			
Results of boot Model has been Means shown bel bootstrap estim below are the o on the full sam bootstrap sampl	reestimated ow are the ates. Coeff riginal est ple.	20 time means of th icients sho imates base	s. e wn d		
Variable  Coeff	icient S	tandard Err	or b/St.Er.	P[ Z >z]	Mean of X
B002	03692***	.00133	-9.545 27.773 -7.431	.0000	

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#### **Bootstrap Replications**

🎟 Matri	ix - Result		
[21, 3]	Cell:		
	1	2	3
1	-79.7535	0.0369204	-15.1224
2	-79.7751	0.0372034	-15.8164
3	-74.4476	0.0362466	-13.7959
4	-95.5803	0.0398037	-20.0141
5	-71.3427	0.0357651	-13.5814
6	-73.1011	0.0356458	-13.1219
7	-72.5021	0.0351552	-11.5075
8	-76.4406	0.0362488	-14.164
9	-77.2569	0.0361277	-13.5284
10	-100.156	0.0399487	-18.7463
11	-75.267	0.0361851	-13.6539
12	-79.4569	0.0366386	-14.0377
13	-82.6841	0.0379192	-18.0799
14	-74.2405	0.0357758	-12.9962
15	-80.2597	0.0369627	-15.2569
16	-75.3873	0.0366071	-14.9952
17	-74.066	0.0359726	-13.6492
18	-69.3163	0.0357294	-15.186
19	-86.3477	0.0376877	-14.9584
20	-95.5345	0.0388132	-15.1778
21	-77.4944	0.0359977	-13.0415
	////////	////////	

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# **Multiple Imputation for Missing Data**

The template application of MI can be drawn with reference to a model

 $y = f(x_1, x_2|\boldsymbol{\beta})$ 

where  $\beta$  is the parameter vector to be estimated. We suppose that there are *n* observations in the sample,  $n_{c,1}$  complete observations on x1,  $n_{m,1}$  missing values for x1, and  $n_{c,2}$  and  $n_{m,2}$  complete and missing observations on x2. The missing and complete observations on x1 and x2 need not coincide. We suppose as well that there is additional information in the sample, **Z**, for which there are observations present for at least some observations when there are missing observations on x1 or x2.

#### **Imputed Covariance Matrix**

The overall approach of MI is to use available information on  $x^2$  and Z to predict missing values of  $x^1$  and available information on  $x^1$  and Z to predict missing values of  $x^2$ . It is assumed that the missing values are 'missing at random,' that is, that the data on  $x^2$  and Z do not contain information on the probability that  $x^1$  is missing, and likewise for  $x^1$  and Z for  $x^2$ . The three steps listed above are carried out as follows:

- Step 1. Construct imputation equations  $\hat{x}_1 = h_1(x_2, Z, \hat{\delta}_1)$  and  $\hat{x}_2 = h_2(x_1, Z, \hat{\delta}_2)$  using available complete observations on relevant variables.
- Step 2. (*M* repetitions): Simulate missing values of x1 from the conditional model  $h_1$  and missing values of  $x_2$  from the conditional model  $h_2$ . For each repetition, we obtain estimates of the parameters,  $\hat{\beta}_m$  and the asymptotic covariance matrix  $\hat{\Sigma}_m$ .

**Step 3.** (Aggregation). The estimator of  $\boldsymbol{\beta}$  is  $\overline{\mathbf{b}} = \frac{1}{M} \sum_{m=1}^{M} \hat{\boldsymbol{\beta}}_{m}$ . The variance estimator is

$$\overline{\mathbf{S}} = \frac{1}{M} \sum_{m=1}^{M} \hat{\boldsymbol{\Sigma}}_{m} + \left(1 + \frac{1}{M}\right) \frac{1}{M-1} \sum_{m=1}^{M} \left(\hat{\boldsymbol{\beta}}_{m} - \overline{\mathbf{b}}\right) \left(\hat{\boldsymbol{\beta}}_{m} - \overline{\mathbf{b}}\right)'$$

#### Implementation

- SAS, Stata: Create full data sets with imputed values inserted. M = 5 is the familiar standard number of imputed data sets.
- NLOGIT/LIMDEP
  - Create an internal map of the missing values and a set of engines for filling missing values
  - Loop through imputed data sets during estimation.
  - M may be arbitrary memory usage and data storage are independent of M.