An Introduction to statistical methods with Stata

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Source of some of the quotes: http://math.furman.edu/~mwoodard/mqs/ascquotg.html

 "[Statistics are] the only tools by which an opening can be cut through the formidable thicket of difficulties that bars the path of those who pursue the Science of Man." **Reportedly from** Pearson, The Life and Labours of Francis Galton, 1914. downloaded from the above source on 30 June 2009.



Introduction to Stata I

- Invocation of Stata
- Why Stata?
 - Best bang for the buck
 - Easier than R or S+
 - Cheaper than SAS
 - Example datasets are free and included
 - Updated regularly from the web
 - SSC program archive
 - Can handle panel data
 - Can handle complex sample analysis
 - Can handle advanced models
 - Web interface
 - Stata list server
 - Stata Journal
 - Users Group meetings
- Approaches to learning Stata
 - Menus for novices
 - Batch for professionals



Grand outline II

- Introduction to Stata --- continued
 - Configuration of Stata (adding your own editor)
 - Free data sources
 - Variable construction (including date and time variables, etc.)
 - Variable transformations (recoding, replacing, functional, and power)
 - Missing value management (single and multiple imputation)
 - Codebook construction
 - Dataset construction: cross-sectional, longitudinal, time series, panel, survival
 - File management (appending and merging, wide-long conversion)
- Data cleaning
 - Range and consistency checks
 - file comparison
- Exploratory graphical visualization Edward Tufte's contribution
 - Histograms, Bar graphs, Line graphs, matrix scatterplots, Pie charts, Panel graphs, and Annotation



Grand Outline-III

Research Project planning concerns

- Power and sample size analysis Jacob Cohen's contribution
- Sampling (simple random, stratified, clustered, stratified -clustered)
- Attrition and censoring in longitudinal studies
- Hypothesis testing
- Item analysis and scale construction
 - Reliability and validity analysis
- Summary statistics for sample description
- Categorical data analysis Leo Goodman's contribution
 - Tabulations
 - Cross-tabulations
 - Statistical tests
- T-tests William Gossett's contribution
 - One-sample
 - Two independent samples
 - Paired



Grand outline IV

- ANOVA contribution of R.A. Fisher
 - Assumptions and tests for them
 - One-way ANOVA
 - Two-way ANOVA
 - Random, Fixed, and Mixed models
 - Repeated Measures WSANOVA
- Regression analysis contributions from Gauss and Legendre
 - Univariate
 - Assumptions and tests for them
 - Modeling strategies and critiques
 - General-to-specific (David F. Hendry Jean Francois Richard) Hierarchical, All possible subsets
 - Robust regression (Halbert White and Huber and others)
 - Heteroscedastically consistent estimation
 - Outlier down-weighting

Bootstrapping regression models Brad Efron's contribution

Grand Outline V if time permits

- Regression analysis with Limited Dependent Variables
 - Poisson count models
 - Logistic and Probit models for binary dependent variables
 - Skewed logistic models
 - Ordered Logistic and Ordered Probit regression models for ordinal dependent variables
 - Multinomial logistic regression models for categorical dependent variables

Configuration, logging, execution, and output

- Configuring your Stata
 - Preferences
 - profile.do command file
 - Logging your own work
 - smcl files
 - Translate command
 - Saving graphs
- Running Stata
 - Saving output
 - Printing output

Configuring Stata:

Double click on Stata icon Stata platform appears



Click Edit, preferences, General Preferences



Select White background and click "OK"

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The Background color is now white



Changing font size in any window

- You may for presentation or personal display, right click on any window, and alter the font size.
- This can make the output easier to read for those who are viewing the output.

Getting help with Stata

- F1 is help
- You can type: help command,
 - where command is any command you need help with for the proper syntax
 - you can type: find keyword on the command line where a keyword will help the search progress among the Stata help files and on the internet
 - You can google a Stata command and get help on the internet

Type: help or help keyword

тор

Category listings

Basics

language syntax, expressions and functions, ...

Data management inputting, editing, creating new variables, ...

Statistics
summary statistics, tables, estimation, ...

Graphics scatterplots, bar charts, ...

Programming and matrices do-files, ado-files, Mata, matrices

Help file listings

Language syntax advice on what to type

Manual datasets download datasets from the Reference manuals

Copyrights

help functions

<u>Title</u>

[D] functions — Functions in expressions

Quick references are available for the following types of functions:

Type of function	See help
Mathematical functions	math functions
Probability distributions and density functions	density functions
Random-number functions	random-number functions
String functions	string functions
Programming functions	programming functions
Date and time functions	dates and times
Selecting time spans	time-series functions
Matrix functions	matrix functions

Introduction

Functions are used in expressions, which are abbreviated exp in syntax diagrams. For example, a simplified version of **generate's** syntax is

generate newvar = exp

and thus, one might type "generate loginc = ln(income)". ln() is a function.

Functions may be specified in any expression. The arguments of a function may be any expression, including other functions.

A function's arguments are enclosed in parentheses and, if there are multiple arguments, separated by commas.

Functions return missing (.) when the value of the function is undefined.

ct=70 naw - cond(cav-"m" "We " "Wc ") + neonae(nama)

Examples

. generate y = sqrt(abs(z*z-x*x-y))

Type: findit keyword

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432 list 433 egen rown 434 egen rown 435 list	FAQ How to perform multiple imputation on longitudinal data using ICE?
436 help functi 437 help 438 findit gam	Example Multiple imputation using ICE 9/06 http://www.ats.ucla.edu/stat/stata/library/ice.htm
440 help lar 441 help var 442 findit multi	Example
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rowm	SJ-5-4 st0067_2 Multiple imputation of missing values: Update of ice (help ice, micombine, mijoin if installed) P. Royston Q4/05 SJ 5(4):SZ7S36 update of mvis (renamed to ice); imputation of missing values now achieved by sampling from the posterior predictive distribution
findit multiple imputation	SJ-5-2 st0067_1 Multiple imputation of missing values: update (help ice, micombine, mijoin if installed) P. Royston Q2/05 SJ 5(2):188201 substantial update to mvis (renamed ice) and some improvements to micombine
Command	SJ-4-3 St0067
C:\Documents and Set 🔢 Stata/MP 10.1 - D:\st 🔩 Ja	isc Paint Shop Pro - I 🔞 How Stata records dat 💌 Viewer (#3) [Help Con 💌 Viewer (#2) [search m

Important Stata Resources

- Stata has excellent manuals
- Stata offers first rate technical support
- Stata can download from the web
- UCLA ATS has excellent Stata help
- It has movies which teach Stata for those who need or wish visual instruction
- Stata Press publishes texts dealing with Stata commands
- It has a list of command examples
- Type: findit keyword on command line while connected to web. Keyword is any name in which you are interested.
- FRED St. Louis Federal Reserve Economic Database : freduse command
- Yahoo
- Economic report to the President

SSC archive

- Be sure you are connected to the www
- Type: ssc describe a
- Type: ssc describe b

Installing from the web

- Suppose you wish to download the datasets and do files from Regression models and categorical variables using Stata by J. Scott Long and Jeremy Freese. You could use the following commands:
- net search spost
- if you are using version 9, you can execute the following commands:
- net get rmcdvs
- net from <u>http://www.indiana.edu/~jslsoc/data</u>
- net get spost9_do
- net install spost9_ado

File construction and data definition

File construction

- Input command
 - Id variables
 - For rectangular datasets
 - For hierarchical datasets
 - Date variables
 - For time series datasets
 - Panel variables and date variables
 - For panel datasets
 - Variable definition
 - Numeric
 - String
 - dates
 - Variable labels
 - Formats
 - Linking formats

Data definition-continued

- missing data management
- Wide files
- Long files
- Save
- Saveold
- Do files
- Ado files

File Construction: for raw data input, the input command can be used

	and the second se	
5112	Variables ×	. mkdir introStata
	Name Label id age gender income	. cd introStata D:\stats\stata10\data\introStata . dir <dir> 5/03/09 0:23 .</dir>
		<pre><dir> 5/03/09 0:23 input id age gender income</dir></pre>
		Command
		4 30 1 11
1	< >	

Type "end" to complete data input

	id	age	gender	income		
1. 2. 3.	1 2 3	23 12 28	0 1 0	5 7 10		
4. inpu 5. 5 6. 6	4 it 5 36 (2nd	id) 12	ag	je ge	ender	income

Command

Accessing a Stata dataset file1.dta with the use command

- dir file1.dta 2.2k 5/03/09 1:58 **file1.dta**
- use file1, clear
- list

	id	age	ages	gender	income	sex	sexn
1.	1	23	23	male	\$20K-24999	0	male
2.	2	12	12	female	\$40k-49999	1	female
3.	3	28	28	male	\$70k-80k	0	male
4.	4	30	30	female	\$80k-90k	1	female
5.	5	36	36	male	\$90k+	0	male
6.	6	34	34	female	-9	1	female

Saving a Stata dataset

- You can type: save filename

 If this is the first time you are saving it.
- You can type: save filename, replace

 If you are replacing an earlier version with a newer one.
- You can type: saveold filename
 If you wish to save it in Stata9 format

Saving a Stata dataset

list

	id	age	ages	gender	income	sex	sexn
1.	1	23	23	male	\$20K-24999	0	male
2.	2	12	12	female	\$40k-49999	1	female
3.	3	28	28	male	\$70k-80k	0	male
4.	4	30	30	female	\$80k-90k	1	female
5.	5	36	36	male	\$90k+	0	male
6.	6	34	34	female	-9	1	female

. save file1, replace file file1.dta saved

Data definition Variable labels

- . label var gender "Sex of respondent"
- . label var income "Income group"

list

	id	age	gender	income
1.	1	23	0	5
2.	2	12	1	7
3.	3	28	0	10
4.	4	30	1	11
5.	5	36	0	12

. tab gender

Sex of respondent	Freq.	Percent	Cum.
0 1	3 2	60.00 40.00	60.00 100.00
Total	5	100.00	

Data definition Value labels or formats

- . label define sx 0 "male" 1 "female"
- . label values gender sx

. tab gender

Sex of respondent	Freq.	Percent	Cum.
male female	3 2	60.00 40.00	60.00 100.00
Total	5	100.00	

tab gender, nolabel

Sex of respondent	Freq.	Percent	Cum.
0 1	32	60.00 40.00	60.00 100.00
Total	5	100.00	

Missing values in Stata

- Missing values in Stata are treated as large positive numbers
- They may be system missing and represented by a.
- They may be 26 other codes from .a to .z
 For missing values analysis.
- Therefore, when executing operations in Stata, you might want to qualify your requests for estimations with the condition if not equal to missing, for example
- list income, if income < .

Stata will omit these system missing values from computations



Variable construction: with generate

When constructing variables, be sure you don't recode the missing into 0 by using an if income < .

generate wealthy = 0 if income < .
replace wealthy = 1 if income < . & income > 7

Dummy Variable construction

Long and Freese, op cit, 68-70.

```
************ Dummy Variable Construction
capture log close
log using isfac, replace
use jobnow, clear
* We construct a dummy variable that is 1 if respondent is faculty and 0 otherwise.
* This can be done in one command:
generate isfac = (jobtype==1) if jobtype < .
tab isfac jobtype, missing
label variable isfac "University faculty member"
label define isfac 0 "not faculty" 1 "faculty"
label values isfac isfac
log close
```

	. tab isfac jobtype, missing									
24 DO	University faculty member	•	Total							
	not faculty faculty ·	0 5 0	2 0 0	3 0 0	1 0 0	0 0 1	6 5 1			
	Total	5	2	3	1	1	12			

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Stata egen functions

The egen rowwise functions all ignore missing values . They will only return a missing if all components are missing. For example:

- egen x123max= rowmax(x1,x2,x3) computes row maximum of the three variables specified.
- egen x123mean=rowmean(x1,x2,x3) computes row mean of x1,x2, and x3.

egen x123total=rowtotal(x1,x2,x3) computes rowtotal of x1,x2, and x3.

egen rowmss = rowmiss(x1,x2,x3,x4) indicates number
of missing values in the row of x1 through x4 variables.

Other Stata egen functions

egen rnk=rank(v1)

Will rank the cases according to variable v1

. egen rnk=rank(price)

list rnk price

	rnk	price
1.	1	3,291
2.	2	3,299
3.	3	3,667
4.	4	3,748
5.	5	3,798
6.	6	3,799
7.	7	3,829
8.	8	3.895

Anycount(varlist), values(numlist) Anyvalue (varlist), values(integer numlist) Mean(varlist) Median(varlist) mode(") creates a constant in a list containing

this statistic

ICD9 codes are stored within

Medical researchers use the international statistical codes for diseases and related health problems

Stata has them built in.

They are regularly updated

You can generate new variables with them or search old variables for elaborated definitions.

"carcinoma" 3 matches found: 232 carcinoma in situ skin* 233.31 carcinoma in situ vagina 233.32 carcinoma in situ vulva icd9 lookup 493 1 match found: 493 asthma* icd9 search "asthma" 19 matches found: 493 asthma* 493.0 extrinsic asthma* 493.00 extrinsic asthma nos 493.01 ext asthma w status asth 493.02 ext asthma w(acute) exac 493.1 intrinsic asthma* 493.10 intrinsic asthma nos 493.11 int asthma w status asth 493.12 int asthma w (ac) exac 493.20 chronic obst asthma nos 493.21 ch ob asthma w stat asth 493.82 cough variant asthma 493.9 asthma nos* 493.90 asthma nos 493.91 asthma w status asthmat 493.92 asthma nos w (ac) exac 975.7 poisoning-antiasthmatics E945.7 adv eff antiasthmatics V17.5 family hx-asthma

Standardization of variables Long and Freese, op. cit., p.96

X standardized coefficients

Suppose you have a regression formula, x-standardization $y = a + b_1 x_1 + b_2 x_2 + \dots + b_k x_k + e$ where

e = error, disturbance, innovation, shock we divide each x_k by σ_k and multiply the b_k by that quantity:

$$y = a + \sigma_1 b_1 \frac{x_1}{\sigma_1} + \sigma_2 b_2 \frac{x_2}{\sigma_2} + \dots + \sigma_k b_k \frac{x_k}{\sigma_k} + e, \text{ so the } x - stdzed$$

coefficient =

$$\beta_1^s = \sigma_1 b_1 \frac{x_1}{\sigma_1}$$
Interpretation of x-standardization

 For a continuous variable, for an increase in one standard deviation of x, the amount of change in the dependent variable, y, holding all other x variables constant, associated with this increase in x is :

• This amount = $\beta^s = \sigma b$

y standardization

 When we divide a continuous dependent variable by its standard deviation, we have to divide the whole equation by the same amount. This is called y standardization.

Y standardization

y-standardization $y = a + b_1 x_1 + b_2 x_2 + \dots + b_k x_k + e$ where *e* = *error*, *disturbance*, *innovation*, *shock* and σ_{v} = standard deviation of the dependent variable. we divide y and each b_k by σ_y : $\frac{y}{\sigma_{y}} = \frac{a}{\sigma_{y}} + \frac{b_{1}}{\sigma_{y}}x_{1} + \frac{b_{2}}{\sigma_{y}}x_{2} + \dots + \frac{b_{k}}{\sigma_{y}}x_{k} + \frac{e}{\sigma_{y}}, \text{ so the } y - stdzed$ *coefficient* = $\beta_k^{s_y} = \frac{b_k}{\sigma_y}$

Interpretation of Y standardization Long and Feeze, op. cit., 97

- For an increase in one unit of x_k, the amount of change in Y associated with that change is β^{sy} standard deviations, holding all other variables constant.
- For a dummy variable having characteristic x as opposed to not having it, the amount of change in Y is β^{sy} standard deviations, holding all other variables constant.

Y standardization with latent variable y* Long and Freese, op. cit.,97

- We divide the whole equation by the standard deviation of y. It is assumed that the variance of the error in a probit model=1.
- To estimate the variance of the latent variable y*, we find that
- Var(y*)= βVar(x)β+Var(e) so that
- Var(y*) *)= βVar(x)β + 1
- Where Var(x)=Covariance matrix of xs from the real data.

Full Standardization

Full-standardization $y = a + b_1 x_1 + b_2 x_2 + \dots + b_k x_k + e$ where *e* = *error*, *disturbance*, *innovation*, *shock* we divide each x_k by σ_k and multiply the b_k by that quantity: $\frac{y}{\sigma_{y}} = \frac{a}{\sigma_{y}} + \sigma_{1}b_{1}\frac{x_{1}}{\sigma_{y}} + \sigma_{2}b_{2}\frac{x_{2}}{\sigma_{y}} + \dots + \sigma_{k}b_{k}\frac{x_{k}}{\sigma_{y}} + \frac{e}{\sigma_{y}}, \text{ so the } x - stdzed$ *coefficient* = $\beta_1^s = \sigma_1 b_1 \frac{x_1}{\sigma_y}$

Interpretation of Full Standardization

- After full standardization, the interpretation of change of the regression coefficient in such a model is:
- "For a standard deviation increase in xi, y is expected to change by deviations, while holding all other variables constant."
- Type: listcoef after running the regression analysis using OLS.

net install spostado

net install spostado

checking **spostado** consistency and verifying not already installed... all files already exist and are up to date.

. webuse auto (1978 Automobile Data)

regress mpg price foreign trunk weight length

Source	SS	df	MS		Number of obs	= 74 = 28.06
Model Residual	1645.8167 797.642756	5 329 68 11.	.163341 7300405		Prob > F R-squared	= 0.0000 = 0.6736 = 0.6496
Total	2443.45946	73 33.	4720474		Root MSE	= 3.4249
mpg	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
price foreign trunk weight length _cons	0000377 -1.563592 0143412 0041565 0837896 50.48901	.0002024 1.305732 .1372338 .0020019 .0627953 6.773436	-0.19 -1.20 -0.10 -2.08 -1.33 7.45	0.853 0.235 0.917 0.042 0.187 0.000	0004415 -4.16914 288187 0081512 2090957 36.97283	.0003661 1.041956 .2595047 0001619 .0415165 64.00519

listcoef, help

regress (N=74): Unstandardized and Standardized Estimates

Observed SD: 5.7855032 SD of Error: 3.4249147

mpg	b	t	P> t	bStdX	bStdY	bStdXY	SDofX
price	-0.00004	-0.186	0.853	-0.1111	-0.0000	-0.0192	2949.4959
foreign	-1.56359	-1.197	0.235	-0.7195	-0.2703	-0.1244	0.4602
trunk	-0.01434	-0.105	0.917	-0.0613	-0.0025	-0.0106	4.2774
weight	-0.00416	-2.076	0.042	-3.2304	-0.0007	-0.5584	777.1936
length	-0.08379	-1.334	0.187	-1.8657	-0.0145	-0.3225	22.2663

b = raw coefficient

t = t-score for test of b=0

P>|t| = p-value for t-test

bStdX = x-standardized coefficient

bStdY = y-standardized coefficient

bStdXY = fully standardized coefficient

SDofX = standard deviation of X

Covariance

 $Covariance = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{n}$ Cov(Xa) = 0 Cov(Xa) = VAR(X) Cov(X'X) = VAR(X) $COV(X'Y) = E(XY) = E(x_i - \overline{x})(y_i - \overline{y})$ $= E(x_i y_i) - E(\overline{x}y_i) - E(x_i \overline{y}) + E(\overline{x}\overline{y})$ $= E(x_i y_i)$

Covariances in Stata

. correlate trunk-displacement, covariance (obs=74)

	trunk	weight	length	turn	displa~t
trunk weight length turn displacement	18.2962 2234.66 69.2025 11.3106 239.087	604030 16370.9 2931.73 63873.5	495.79 84.6609 1707.76	19.3543 313.832	8434.07

Francis Galton

 Invented the correlation coefficient and laid the groundwork for regression analysis.



Francis Galton

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Karl Pearson



He read mathematics at Cambridge University in the latter 19th Century. His name is attached to the Chi-square goodness of fit test and the Pearson correlation coefficient. Francis Galton invented the correlation coefficient, but it was named after Karl Pearson.

Pearson product-moment correlations

 Used when both variables are continuous or highly ordinal (with 15 or more levels)



Covariances and Correlations

. correlate trunk-displacement, means (obs=74)

Variable	М	ean St	d. Dev.	Ν	4in	Мах
trunk weight length turn displacement	13.75 3,019 187.9 39.64 197.2	676 4 0.46 7 1324 2 865 4 1973 9	. 277404 77. 1936 2. 26634 . 399354 1. 83722	1,	5 760 142 31 79	23 4,840 233 51 425
	trunk	weight	length	turn	displa~t	
trunk weight length turn displacement . correlate tr	1.0000 0.6722 0.7266 0.6011 0.6086	1.0000 0.9460 0.8574 0.8949 cement, c	1.0000 0.8643 0.8351	1.0000 0.7768	1.0000	
(obs=74)	trunk	weight	length	turn	displa~t	
trunk weight length turn displacement	18.2962 2234.66 69.2025 11.3106 239.087	604030 16370.9 2931.73 63873.5	495.79 84.6609 1707.76	19.3543 313.832	8434.07	

Francis Galton: the father of Correlations

correlate computes listwise correlations

pwcorr computes pairwise correlations, though there is a listwise option. You can also get nobs and sig as options for this command.





Pairwise correlations

. pwcorr mpg trunk-turn, sig obs sidak print(05) star(05)

	mpg	trunk	weight	length	turn
mpg	1.0000				
	74				
trunk	-0.5816*	1.0000			
	74	74			
weight	-0.8072* 0.0000	0.6722* 0.0000	1.0000		
	74	74	74		
length	-0.7958* 0.0000	0.7266* 0.0000	0.9460* 0.0000	1.0000	
	74	74	74	74	
turn	-0.7192* 0.0000	0.6011* 0.0000	0.8574* 0.0000	0.8643* 0.0000	1.0000
	74	74	74	74	74

Properties of Pearson Correlations

- They measure only the significance, direction, and strength of linear relationships. They are not designed to work with binary or ordinal variables.
- If the relationship is quadratic or mostly nonlinear, these correlations may not detect them.
- Therefore, do scattergrams between the two variables first.
- Then do a lowess plot to detect nonlinearity in the relationship.

Charles Spearman's p correlation for ordinal variables Stata Release 10 Reference Manual Q-Z, (2007). College Station, Tx: StataCorp, 321.



 Spearman's rho was named after Charles Spearman, who used ranks to compute the correlation formula and handled ties with average ranks of the ordinal variables.

Spearman's
$$\rho_{yx} = \mathbf{1} - \frac{\mathbf{6}\sum d_i^2}{n(n^2 - \mathbf{1})}$$

where

 d_i = difference between ranks of corresponding values of X_i and Y_i

Significance testing.

Significance tested with

$$p = 2 * ttail\left(n-2, \frac{|\hat{\rho}|\sqrt{n-2}}{\sqrt{1-\hat{\rho}^2}}\right)$$

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Spearman correlations for ordinal variables

spearman mpg trunk-disp, stats(rho obs p) star(.05) sidak Кеу rho Number of obs sig. level trunk weight length turn disp mpg 1.0000 mpg 74 trunk -0.6498* 1.0000 74 74 0.0000 weight -0.8576* 0.6564* 1.0000 74 74 74 0.0000 0.0000 length -0.8314* 0.7191* 0.9490* 1.0000 74 74 74 74 0.0000 0.0000 0.0000 -0.7577* 0.6204* 0.8598* 0.8824* 1.0000 turn 74 74 74 74 74 0.0000 0.0000 0.0000 0.0000 disp -0.7713* 0.5766* 0.9054* 0.8525* 0.7792* 1.0000 74 74 74 74 74 74 0.0000 0.0000 0.0000 0.0000 0.0000

Sir Maurice George Kendall's rank correlations : Tau a and Tau b

Stata Reference Release 10, Manual R-Z, StataCorp, College Station, Tx: 321-322.

 $\tau_a = \frac{\sum (C-D)}{n(n-2)/2}$

$$\tau_b = \frac{\sum (C - D)}{\sqrt{N - U\sqrt{N - V}}}$$

where

•

$$N = n(n-2)/2$$



 $U = \sum_{i=1}^{N_I} u_i (u_i - 1) / 2 \text{ with } N_I = \# \text{ sets of tied x values}$

 $u_i = #tied x values in the ith set$

 $V = \sum_{j=1}^{N_2} v_j (v_i - \mathbf{I}) / \mathbf{2} \text{ with } N_2 = \# \text{ sets of tied y values}$

 $v_{i} = \# tied y values in the jth set.$ Copyright @2009 Robert Alan Yaffee, Ph.D.

Kendall's correlation for ordinal variables (*Ibid*)

ktau mpg trunk-disp, stats(taua taub score se obs p) star(.05) bonferroni pw

Кеу
tau_a tau_b score se of score Number of obs sig. level

	mpg	trunk	weight	length	turn	disp
mpg	0.9471 1.0000 2558.0000 212.9891 74					
trunk	-0.4509* -0.4808* -1.22e+03 212.5833 74 0.0000	0.9289 1.0000 2509.0000 212.1798 74				
weight	-0.6857* -0.7059* -1.85e+03 213.6052 74 0.0000	0.4521* 0.4699* 1221.0000 213.1941 74 0.0000	0.9963 1.0000 2691.0000 214.2359 74			

Kendall's Corr significance tests

 Stata Base Release 10, 2007, Reference Manual, Q-Z, StataCorp, College Station, Tx, 322.

$$z = \frac{|S|}{\sqrt{Var(S)}} \text{ or } z = \frac{|S| - 1}{\sqrt{Var(S)}} \text{ if a continuity correction is desired}$$

where

Assume $S = \sum C - \sum D$

$$Var(S) = \frac{1}{18} \left\{ n(n-1)(2n+5) - \sum_{i=1}^{N_{i}} u_{i}(u_{i}-1)(2u_{i}+5) - \sum_{i=1}^{N_{2}} v_{i}(v_{i}-1)(2v_{i}+5) \right\}$$
$$+ \frac{1}{9n(n-1)(n-2)} \left\{ \sum_{i=1}^{N_{i}} u_{i}(u_{i}-1)(u_{i}-2) - \sum_{i=1}^{N_{2}} v_{i}(v_{i}-1)(v_{i}-2) \right\}$$
$$+ \frac{1}{2n(n-1)} \left\{ \left\{ \sum_{i=1}^{N_{i}} u_{i}(u_{i}-1) \right\} \left\{ \sum_{i=1}^{N_{2}} v_{i}(v_{i}-1) \right\} \right\}$$

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Tetrachoric Correlations for Binary Variables.

Stata Release 10 Base Reference Manual (2007). College Station, Tx.: StataCorp, 480.

$$\rho_{tetrachoric} = \frac{\alpha - 1}{\alpha + 1}$$

where

$$\alpha = \left(\frac{n_{00} n_{11}}{n_{01} n_{10}}\right)^{\pi}$$

$$avar(\hat{\rho}) = \left(\frac{\pi\alpha}{2(1+\alpha)^2}\right)^2 \left(\frac{1}{n_{00}} + \frac{1}{n_{01}} + \frac{1}{n_{10}} + \frac{1}{n_{11}}\right)$$

all $n_{ij} > 0$

Tetrachoric correlations for binary variables

. correlate d1 d2 (obs=1000)

	d1	d2
d1 d2	1.0000 0.1534	1.0000

. tetrachoric d1 d2

Number of obs =	1000
Tetrachoric rho =	0.4432
Std error =	0.0736

Test of Ho: d1 and d2 are independent 2-sided exact P = **0.0000**

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Checking the dataset for missing values

. misschk				
Variables exami	ined for mis	ssing va	lues	
# Variable	# M1	issing	% Mis	sing
1 id 2 jobtype 3 worknow 4 isfac		0 1 1 1	0 8 8 8	.0 .3 .3 .3
Missing for which variables?	Freq.	Pero	ent	Cum.
_2_4 3_	1 1 10	83 83	3.33 3.33 3.33	8.33 16.67 100.00
Total	12	100	0.00	
Missing for how many variables?	Freq.	Pero	ent:	Cum.
0 1 2	10 1 1	83 8 8	3.33 3.33 3.33	83.33 91.67 100.00
Total	12 Copyright @2	100 009 Rober). 00 t Alan Yaff	ee, Ph.D.

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Detecting missing value patterns

. mvpatterns variables with no mv's: id

Variable	type	obs	mv	variable label
jobtype	byte	11	1	What is the type of job you have now?
worknow	byte	11	1	Are you working now?
isfac	double	11	1	University faculty member

Patterns of missing values

_pattern	_mv	_freq
+++	0	10
+.+	1	1
.+.	2	1

Recoding missing values

- mvdecode and mvencode commands
- mvdecode permits you to recode various values of a variable to missing.
- mvencode permits you to recode missing values to a nonmissing value. For example: mvencode income, mv(-9=.a)

mvencode: converting from special to numeric missing value codes

mvencode income, mv(.a=-9)
income: 1 missing value recoded

list

id	age	gender	income
 1	23	male	\$20K-24999
2	12	female	\$40k-49999
3	28	male	\$70k-80k
4	30	female	\$80k-90k
5	36	male	\$90k+
6	34	female	-9

Mvdecoding: converting from one to another missing value codes

list

	id	age	gender	income
1.	1	23	male	\$20K-24999
3.	3	28	male	\$70k-80k
4. 5.	4 5	30 36	female male	\$80k-90k \$90k+
6.	6	34	female	-9

mvdecode income, mv(-9=.a)
 income: 1 missing value generated

list

	id	age	gender	income
. [1	23	male	\$20K-24999
	2	12	female	\$40k-49999
	3	28	male	\$70k-80k
	4	30	female	\$80k-90k
	5	36	male	\$90k+
	6	34	female	.a

Missing value replacement

- Stata can perform multiple imputation the its mice procedure developed by Patrick Royston.
- It is available as a free download from Stata Software Components archive
- ssc install mice can be typed on the command line.

Variable transformation: **Recoding variables** recode income (1/3=1)(4/6=2)(7/12=3) or generate incgrp = 1replace incgrp=2 if income > 3 | income < 8 replace incgrp = 3 if income > 6 & income < .

Variable formats

- String: alpha %9s
- Numeric: numeric %8.2g
- Date : day %td, week %tw, month %tm, quarter %tq, year %ty
- Panel: it where i=group and t = date

Variable format conversion: from string to numeric

🗖 Data Editor							
Preserve Restore Sort << >> Hide Delete							
sex[1] =							
	id	age	gender	income	sex		
1	1	23	male	\$20K-24999	m		
2	2	12	female	\$40k-49999	f		
3	3	28	male	\$70k-80k	m		
4	4	30	female	\$80k-90k	f		
5	5	36	male	\$90k+	m		
6	6	34	female	f f			
				Variable Properties			
				Name:			
				sex			
				Label:			
				sex of respon	sex of respondent		
				Format:	Format		
				~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	- %9s		
				-			
					Value label		
				<none></none>	- <none></none>		
				Define/Mo	Define/Modify		
					Οκ	Cana	
							3

## Converting a numeric to a string variable

. tostring age, gen(ages) ages generated as **str2** 

. list

	id	age	ages	gender	income
1.	1	23	23	male	\$20K-24999
2.	2	12	12	female	\$40k-49999
3.	3	28	28	male	\$70k-80k
4.	4	30	30	female	\$80k-90k
5.	5	36	36	male	\$90k+
6.	6	34	34	female	-9

### Variable format conversion: converting numeric to string


### Variable transformation: converting string to numeric variables

#### list

	id	age	ages	gender	income	sex	sexn
1.	1	23	23	male	\$20K-24999	0	0
2.	2	12	12	female	\$40k-49999	1	1
3.	3	28	28	male	\$70k-80k	0	0
4.	4	30	30	female	\$80k-90k	1	1
5.	5	36	36	male	\$90k+	0	0
6.	6	34	34	female	-9	1	1

label values sexn sx

list

id	age	ages	gender	income	sex	sexn
1	23	23	male	\$20K-24999	0	male
2	28	28	male	\$70k-80k	0	male
4 5	30 36	30 36	female male	\$80k-90k \$90k+	1	female male
6	34	34	female	-9	1	female
	id 1 2 3 4 5 6	id age 1 23 2 12 3 28 4 30 5 36 6 34	id age ages 1 23 23 2 12 12 3 28 28 4 30 30 5 36 36 6 34 34	id     age     ages     gender       1     23     23     male       2     12     12     female       3     28     28     male       4     30     30     female       5     36     36     male       6     34     34     female	id       age       ages       gender       income         1       23       23       male       \$20K-24999         2       12       12       female       \$40k-49999         3       28       28       male       \$70k-80k         4       30       30       female       \$80k-90k         5       36       36       male       \$90k+         6       34       34       female       -9	id       age       ages       gender       income       sex         1       23       23       male       \$20K-24999       0         2       12       12       female       \$40k-49999       1         3       28       28       male       \$70k-80k       0         4       30       30       female       \$80k-90k       1         5       36       36       male       \$90k+       0         6       34       34       female       -9       1

### **Exercises** 1

- 1. Get help on the egen command within Stata
- 2. Use the findit command to obtain help on a keyword of interest
- 3. Get help on datasets available
- 4. Download from the web the lifeexp.dta dataset
- 5. Describe the dataset
- 6. Use the inspect command to check for missing values
- 7. Examine the variables for missing values
- 8. Give the variable safewater a variable label.
- 9. Do a frequencies analysis on the variable, safewater
- 10. List the countries with 100% safewater

### **Exercises 1 continued**

- 1. List countries with less than 75% safewater
- 2. List countries with more than 75% and less than 96% safewater
- 3. List countries with less than 10% population growth
- 4. Download bpwide.dta from web
- 5. Crosstabulate sex and agegroup (show counts, row and column percentages)
- 6. What is the Pearson correlation between the blood pressure before and after?
- 7. Is this a significant correlation?
- 8. Is this a linear relationship?
- 9. Construct your own dataset with 3 discrete variables and 2 continuous variables with 5 observations. Label the variables and the values of the discrete variables. Tabulate the variables. Crosstabulate two of the discrete variables and obtain a chi-square test for significance between them. If they are ordinal obtain a Gamma and a Kendall's tau a correlation between them.
- 10. Construct a variable that gives the row average of three of your variables in that dataset. Be sure that this variable does not use missing values.

### A comment by Hadamard

Hadamard, Jacques

- The shortest path between two truths in the real domain passes through the complex domain.
- Quoted in The Mathematical Intelligencer, v. 13, no. 1, Winter 1991.

### File management

Codebook construction inspection recoded variables tabulations summaries missing value analysis basic histograms and boxplots File merging File appending **File conversion** from wide to long from long to wide Construction of special files Time series datasets Panel datasets Survival datasets complex survey analysis **Do Files** Ado Files

### Import- export

### Importing data

- Transferring data from excel
- Insheet command with raw files
- Statransfer
- DBMSCopy
- Exporting data
  - Saveasas
  - Save as excel
  - Save as access
  - Statransfer
  - DBMSCopy

### Importing data

- From ascii text
- From spreadsheet files
- from other statistical packages
  - With stat transfer
  - With dbmscopy

### Importing data from ascii text files

cat text.txt id name age gender 1 jones 12 1 2 smith 11 0 3 phillips 23 1 4 willard 14 0 5 harrison 18 1 6 baum 21 0 7 binley 20 1 8 hanson 20 0 9 nason 191 . infile id str8 name age gender using text.txt, automatic 'id' cannot be read as a number for id[1] 'age' cannot be read as a number for age[1] 'gender' cannot be read as a number for gender[1] (10 observations read) describe Contains data obs: 10 vars: 4 400 (99.9% of memory free) size: storage display value variable name label variable label type format id double %10.0g str8 %9s name double %10.0g age gender double %10.0g Sorted by: Note: dataset has changed since last saved

### **Post-importation refinement**

. list

	id	name	age	gender
1.		name		
2.	1	jones	12	1
3.	2	smith	11	0
4.	3	phillips	23	1
5.	4	willard	14	0
6.	5	harrison	18	1
7.	6	baum	21	0
8.	7	binley	20	1
9.	8	hanson	20	0
10.	9	nason	19	1

. drop if _n==1 (1 observation deleted)

. list

	id	name	age	gender
1.	1	jones	12	1
2.	2	smith	11	0
3.	3	phillips	23	1
4.	4	willard	14	0
5.	5	harrison	18	1
6.	6	baum	21	0
7.	7	binley	20	1
8.	8	hanson	20	0
9.	9	nason	19	1

### **Transferring from Excel to Stata**

 This is performed with a copy and paste operation. Suppose we have an excel worksheet 97-2003 file: excel1.xls

2	excel1.xls					
	Α	В	С	D	E	
1	id	gender	age	incgrp		
2	1	0	23	1		
3	2	1	36	2		
4	3	0	24	3		
5	4	1	32	3		
6	5	0	19	1		
7	6	1	20	1		
8	7	0	40	3		
9						
40						

# We can select all and paste it into a Stata datasheet

Be sure your data are cleared out. On the command line, type: edit A data editor opens below

Data Editor	🔳 Data Ed
Preserve Restore Sort << >> Hide Delete	Preserve
 var1[1] =	
Image: A set in the set in t	

## Select your data including the first line on which the variable names are contained. Right click on copy:

	excel1.xis				
	А	В	С	D	E
1	id	gender	age	incgrp	
2	1	0	23	1	
3	2	1	36	2	
4	3	0	24	3	
5	4	1	32	3	
6	5	0	19	1	
7	6	1	20	1	
8	7	0	40	3	
9					
10					
11					

CON

# Paste in row1 column1 the selected data

Data Editor					
Preserve	Restore Sort		>> Hide	Delete	
		var1[1] =			
	<u>С</u> ору		]		
	<u>P</u> aste				
	Variable	+			
	Select Value f Assign Value I	rom Value Label 🕨			_
	Define/Modify Hide All Value	Value Labels Labels			
	P <u>r</u> eferences				
					Children of the local division of the

## The data are pasted into the Stata data editor, click on preserve, and x out

🗖 Data Editor						
Preserve	Preserve Restore Sort << >> Hide Delete					
		id	[1] = 🚺			
	id	gender	age	incgrp		
1	1	0	23	1		
2	2	1	36	2		
3	3	0	24	3		
4	4	1	32	3		
5	5	0	19	1		
6	6	1	20	1		
7	7	0	40	3		

## The data set is preserved in Stata. Save the file with the save filename command.

~
×
Label

list

	id	gender	age	incgrp
1. 2.	1 2	0 1	23 36	1 2
3. 4.	3	01	24 32	3
5. c	5	0	19	1
6. 7.	7	0	20 40	3

. save file2 file file2.dta saved

# Importing an Excel file with ODBC MS open database connectivity

- Save the excel file as file1.xls
- Go to administrative tools in the control panel and select the odbc options
- Setup the odbc dsn options in the control panel to include file1.xls

🗊 ODBC Data Source A	dministrator	₽?⊠			
User DSN System DSN	File DSN   Drivers   Tracing   Connection	Pooling About			
Name dBASE Files Excel Files Excel 1 xls file 1 xls MS Access Database Visual FoxPro Database Visual FoxPro Tables	Driver Microsoft dBase Driver (*.dbf) Microsoft Excel Driver (*.ds) Microsoft Excel Driver (*.ds, *.dsx, *.dsm, * Microsoft Excel Driver (*.ds, *.dsx, *.dsm, * Microsoft Access Driver (*.mdb) Microsoft Visual FoxPro Driver Microsoft Visual FoxPro Driver	A <u>d</u> d <u>R</u> emove <u>C</u> onfigure			
An ODBC User data source stores information about how to connect to the indicated data provider. A User data source is only visible to you, and can only be used on the current machine.					
Сор	yright @ 2009 Robert Alan	Yaffee, Ph.D.			

### In Stata, confirm listing

- Confirm this by going back into Stata and typing:
- odbc list and being able to see your file in the list.

. Odbc list	
Data Source Name	Driver
Visual FoxPro Tables Visual FoxPro Database MS Access Database Excel Files dBASE Files Excel1.xls file1.xls Xtreme Sample Database 11	Microsoft Visual FoxPro Driver Microsoft Visual FoxPro Driver Microsoft Access Driver (*.mdb) Microsoft Excel Driver (*.xls) Microsoft dBase Driver (*.dbf) Microsoft Excel Driver (*.xls, *.xlsx, *.xl Microsoft Excel Driver (*.xls, *.xlsx, *.xl Microsoft Access Driver (*.mdb)

### This will import the file to Stata

odbc load id=id age gender incgrp, table("Sheet1\$") dsn("file1.xls") list

	id	age	gender	incgrp
1. 2. 3. 4. 5.	1 2 3 4 5	23 36 24 32 19	0 1 0 1 0	1 2 3 3
6. 7.	6 7	20 40	1 0	1 3

### **Exporting data files**

- To other statistical packages

   With DBMScopy
   With Statransfer
- Raw data files

### Exporting a raw data file

. outfile id age ages gender income sexn using file2out

dir			
<dir></dir>	5/03/09	2:00	
<dir></dir>	5/03/09	2:00	
2.2k	5/03/09	1:58	file1.dta
0.3k	5/03/09	1:59	file1out.out
0.4k	5/03/09	2:00	file2out.raw

type file2out.raw

1	23	"23"	"male"	"\$20K-24999"	"male"
2	12	"12"	"female"	"\$40k-49999"	"female"
3	28	"28"	"male"	"\$70k-80k"	"male"
4	30	"30"	"female"	"\$80k-90k"	"female"
5	36	"36"	"male"	"\$90k+"	"male"
6	34	"34"	"female"	-9	"female"

### outsheet using file1out

#### list

	id	age	ages	gender	income	sex	sexn
1.	1	23	23	male	\$20K-24999	0	male
2.	2	12	12	female	\$40k-49999	1	female
3.	3	28	28	male	\$70k-80k	0	male
4.	4	30	30	female	\$80k-90k	1	female
5.	5	36	36	male	\$90k+	0	male
6.	6	34	34	female	-9	1	female

```
pwd
```

D:\stats\stata10\data\introStata

save file1 file file1.dta saved

outsheet id age ages gender income sex sexn using file1out

dir

<dir> 5/03/09 1:59 . <dir> 5/03/09 1:59 ... 2.2k 5/03/09 1:58 file1.dta 0.3k 5/03/09 1:59 filelout.out

	type file1ou	t.out					
i	d age	ages	gender income	e sex	sexn		
1	23	"Ž3"	"male" "\$20к-	-24999"	"0"	"male"	
2	12	"12"	"female"	"\$40k	-49999"	"1"	"female"
3	28	"28"	"male" "\$70k-	-80k"	"0"	"male"	
4	30	"30"	"female"	"\$80k	-90k"	"1"	"female"
5	36	"36"	"male" "\$90k-	+" "0"	"male"		
6	34	"34"	"female"	-9	"1"	"female	

### Accessing example datasets

### Type: help datasets

Viewer (#1) [help dta_contents]	iewer (#1) [help dta_contents]					
🔶 🏟 🚱 🚔 help dta_contents	R					
Advice Contents What's New News						
help dta contents						

#### <u>Title</u>

[U] 1.2.1 Sample datasets

#### **Description**

#### Example datasets installed with Stata

This page contains links enabling you to describe or use the datasets that were installed with Stata.

#### Stata 10 manual datasets

This page provides web access to all the datasets referred to in the Stata documentation.

### On command line: type: webuse auto

	<	>	
-	Variables	×	•
	Name	Label	
	make price mpg rep78 headroom trunk weight length turn displacement gear_ratio foreign	Make and I Price Mileage (m Repair Rec Headroom Trunk spac Weight (bs Length (in. Turn Circle Displaceme Gear Ratio Car type	. clear . webuse auto (1978 Automobile Data)
			Command
1		>	
	D:\stats\stata10\data	a∖introStata	

### **Combining datasets**

- Appending: adding cases to the same variables
- Merging: adding variables to the same cases
- Mixtures
- Caveats: be sure that the missing values are coded the same and designated missing
- Sort both datasets by the same variables before combining.

### **Appending datasets**

 Adding cases to the same variables can be done with the append command. This concatenates the data.

. use append1, clear

#### list

	id	age	gender	inc
1.	1 2	23	0	30000
2.		34	1	40000
3.	3	54	0	45000
4.	4	36	1	47000

. append using append2

#### . list

	id	age	gender	inc
1.	1	23	0	30000
2.	2	34	1	40000
3.	3	54	0	45000
4.	4	36	1	47000
5.	5	34	1	40000
6.	6	40	0	23000
7.	7	36	0	50000
8.	8	48	1	38000

### Merging datasets

#### list

	id	age	gender	inc
1.	1	23	0	30000
2.	2	34	1	40000
3.	3	54	0	45000
4.	4	36	1	47000
5.	5	34	1	40000
6.	6	40	0	23000
7.	7	36	0	50000
8.	8	48	1	38000

#### merge using merge2

list

	id	age	gender	inc	height	educ	_merge
	1 2 3 4 5	23 34 54 36 34	0 1 0 1 1	30000 40000 45000 47000 40000	54 62 65 67 57	0 2 1 3 2	3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
5.	6 7 8	40 36 48	0 0 1	23000 50000 38000	60 59 67	4 2 1	3 3 3

### Reshaping files: Wide to long and Long to Wide

. * Reshaping from wide to long data structure . list

	id	pretest	posttest	followup	age	gender
1.	1	10	14	18	20	m
2.	2	11	17	21	21	f
3.	3	14	15	16	20	m
4.	4	17	19		19	f
5.	5	15	20	23	20	m

```
* Reshaping from wide to long data structure
list
rename pretest time1
rename posttest time2
rename followup time3
reshape long time, i(id)
list
```

	ez times	->	time	
j variable (3 values) xij variables:		->	_j	
Number of obs. Number of variables	5 6	-> ->	15 5	
Data	wide	->	long	
. reshape long time, i(id) (note: j = 1 2 3)				
. rename followup time3				
. rename posttest time2				
. rename pretest time1				

end of do-file

Copyright @2009 Robert Alan Yaffee, Ph.D.

# Output of reshape from wide to long (person-period dataset)

list

	id	_j	time	age	gender
1. 2. 3. 4. 5.	1 1 2 2	1 2 3 1 2	10 14 18 11 17	20 20 20 21 21	m m f f
6. 7. 8. 9. 10.	2 3 3 3 4	3 1 2 3 1	21 14 15 16 17	21 20 20 20 19	f m m f
11. 12. 13. 14. 15.	4 4 5 5 5	2 3 1 2 3	19 15 20 23	19 19 20 20 20	f f m m

### Reshape from long to wide

. list

	id	_j	time	age	gender
1. 2. 3. 4. 5.	1 1 2 2	1 2 3 1 2	10 14 18 11 17	20 20 20 21 21	m m f f
6. 7. 8. 9. 10.	2 3 3 3 4	3 1 2 3 1	21 14 15 16 17	21 20 20 20 19	f m m f
11. 12. 13. 14. 15.	4 4 5 5 5	2 3 1 2 3	19 15 20 23	19 19 20 20 20	f f m m

#### Stata Do-File Editor - wide2long.do

<u>File Edit Search Tools</u>

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#### 📋 wide2long.do

* Reshaping from long to wide list reshape wide time, i(id) j(_j) list

## Output from reshaping from long to wide

(note: j = 1 2 3)			
Data	long	->	wide
Number of obs. Number of variables j variable (3 values) xii variables:	15 5 _j	-> -> ->	5 6 (dropped)
	time	->	time1 time2 time3

list

	id	time1	time2	time3	age	gender
1.	1	10	14	18	20	m
2.	2	11	17	21	21	f
3.	3	14	15	16	20	m
4.	4	17	19		19	f
5.	5	15	20	23	20	m

reshape wide time i(id) i( i)

### sort var1 var2

 You may reorganize your data with a sort command. You may sort by a series of variables.

### Data management

Data management Data cleaning range checks with tabulate summary statistics with summarize consistency checks with pwcorr file comparison utilities

Codebook maintenance

.

- Summary statistics
- Recoded variables
- New variables
- Multiple sorts
- Basic graphs
- Missing values
- Variable transformations
  - Rename
  - Recode
  - Replace if
  - Generate if
  - Egen
  - List if
- Missing value management
  - Storage as very large numbers
  - Mvdecode
  - Mvencode
  - Drop
  - Keep
  - Imputation
    - Single
    - Multiple with mice
- Log files contain time and date
  - Headers
  - Why use log files?
  - Need to keep record and log of work

### We wish to examine the dataset

### • Type: describe

describe

Contains data obs: vars: size:	from htt 74 12 3,774 (	p://www.s	memory free)	/data/r10/auto.dta 1978 Automobile Data 13 Apr 2007 17:45 (_dta has notes)
variable name	storage type	display format	value label	variable label
make price mpg rep78 headroom trunk weight length turn displacement gear_ratio foreign	str18 int int float int int int float byte	%-18s %8.0gc %8.0g %6.1f %8.0g %8.0gc %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g	origin	Make and Model Price Mileage (mpg) Repair Record 1978 Headroom (in.) Trunk space (cu. ft.) Weight (lbs.) Length (in.) Turn Circle (ft.) Displacement (cu. in.) Gear Ratio Car type

Sorted by: foreign

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### Data Scan: reveals histograms and missing data.

#### Type: inspect on the command line



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### Inspect-continued

weight: Weight (lbs.)	
# #	Negative
# #	Zero
# # # # # # # #	Positive
# # # #	Total
# # # # #	Missing
760 4840 (64 unique values)	
ength: Length (in.)	
# #	Negative
# #	Positive
# # #	
# # # # #	Total
# # # # #	Missing
42 233 (47 unique values)	
urn: Turn Circle (ft.)	
	Negative
# #	Zero
# # #	Positive
# # #	_
# # # #	Total
# # # # .	MISSING
L 51	
(4.0	

Nur	mber of Obse	ervations
Total	Integers	Nonintegers
-	-	-
-	-	-
74	74	-
74	74	-
-		
74		

#### Number of Observations

Total	Integers	Nonintegers
-	-	-
_	-	-
74	74	-
74	74	-
-		
74		

#### Number of Observations

Total	Totogong	Nonintegens
TOLAT	incegers	Nonincegers
-	-	-
		-
74	74	-
74	74	-
-		
74		

### codebook command

Results	5							
eadroon	n						Headroom	n (in.)
	type:	numeric ( <b>float</b> )						
	range: unique values:	[1.5,5] 8		units: missing .:	.1 0/74			
	tabulation:	Freq. Value 4 1.5 13 2 14 2.5 13 3 15 3.5 10 4 4 4.5 1 5						
runk						Trun	k space (ci	J. ft.
	type:	numeric ( <b>int</b> )						
	range: unique values:	[5,23] 18		units: missing .:	1 0/74			
	mean: std. dev:	13.7568 4.2774						
	percentiles:	10% <b>8</b>	25% 10	50% 14	75% <b>17</b>	90% <b>20</b>		
eight							Weight	(1bs.
	type:	numeric ( <b>int</b> )						
	range:	[1760, 4840]		units:	10			
### **Codebook command-continued**

						A DISCOURSE OF THE PARTY OF	
I	Results						الكالك
	range: unique values:	[79, 425] 31		uni missing	ts: 1 .: 0/74		
	mean: std. dev:	197.297 91.8372					
	percentiles:	10% 97	25% <b>119</b>	50% <b>196</b>	7 5% <b>250</b>	90% <b>350</b>	
							Gear Ratio
I	<u> </u>						
	type:	numeric <b>(floa</b>	t)				
	range: unique values:	[2.19, 3.89] 36		uni missing	ts: .01 .: 0/74		
	mean: std. dev:	3.01486 .456287					
	percentiles:	10% <b>2.43</b>	25% <b>2.73</b>	50% <b>2.955</b>	75% <b>3.37</b>	90% <b>3.72</b>	
	foreign						Car type
I							
	type: label:	numeric ( <b>byte</b> origin	)				
	range: unique values:	[0,1] 2		uni missing	ts: 1 .: 0/74		
	tabulation:	Freq. Numer 52 22	ic Labe O Dome 1 Fore	l stic ign			

## Data cleaning

- codebook
- inspect
- list
- assert
- count
- extremes
- duplicates
- format
- Missing functions
- Range checks with tabulate
- Consistency checks with correlate or pwcorr
- File comparison utilities

### We can list out data

#### list make

	make
1.	AMC Concord
2.	AMC Pacer
3.	AMC Spirit
4.	Audi 5000
5.	Audi Fox
6.	BMW 320i
7.	Buick Century
8.	Buick Electra
9.	Buick LeSabre
10.	Buick Opel
11.	Buick Regal
12.	Buick Riviera
13.	Buick Skylark
14.	Cad. Deville
15.	Cad. Eldorado
16.	Cad. Seville
17.	Chev. Chevette
18.	Chev. Impala
19.	Chev. Malibu
20.	Chev. Monte Carlo
21.	Chev. Monza
22.	Chev. Nova
23.	Datsun 200
24.	Datsun 210
25.	Datsun 510
26. 27. _more	Datsun 810 Dodge Colt

. list make if _n < 10 | _n > _N-10

in the		make
the all we want	1. 2. 3. 4. 5.	AMC Concord AMC Pacer AMC Spirit Audi 5000 Audi Fox
	6. 7. 8. 9. 64.	BMW 320i Buick Century Buick Electra Buick LeSabre Pont. Sunbird
	65. 66. 67. 68. 69.	Renault Le Car Subaru Toyota Celica Toyota Corolla Toyota Corona
	70. 71. 72. 73.	VW Dasher VW Diesel VW Rabbit VW Scirocco

Double data entry and file comparison

 We can have 2 people enter the data and then compare the files to see if they differ.

. cf2 make-id using auto2, id(id)

. cf2 make-id using auto1, id(id) master has **73** obs., using **74** 

# We can check for extreme values of a variable

extremes	price
obs:	price
45.	3,291
17.	3,299
21.	3,667
68.	3,748
66.	3,798
53.	12,990
38.	13,466
37.	13,594
15.	14,500

16.

15,906

# Checking for duplication of observations: duplicates report

. duplicates report

Duplicates in terms of all variables

copies	observations	surplus
1	6	0

### **Missing values Review**

- Be sure missing values are properly coded for your purposes.
- gen mymis= missing(var1-var10) constructs variable, mymis, which is coded 1 for a line on which any of these variables has a missing value and 0 for a case with no missing values.
- egen rowm = rowmis(var1-var10)
- count if a==. | b==. | c==.

## Missing value functions-continued

. cour 2	nt if	C ==	⁼.						
. count if a ==.   b==.   c ==. 5									
. list									
	id	a	b	c	mymis				
1.	1	3		4	1				
2.	2	4	3	3	0				
3.	3	2	5	1	0				
4.	4	•	•	-	1				
5.	5	4	4	1	0				
6.	6	5		2	1				
7.	7	6	3	3	0				
8.	8		2	4	1				
9.	9	1	1	5	0				
10.	10	2	8	•	1				

egen rowm = rowmiss(a-c)

list

	id	а	b	C	mymis	rowm
1. 2. 3. 4. 5.	1 2 3 4 5	3 4 2	3 5 4	4 3 1	1 0 0 1 0	1 0 3 0
6. 7. 8. 9. 10.	6 7 8 9 10	5 6 1 2	3 2 1 8	2 3 4 5	1 0 1 0 1	1 0 1 0 1

### Inspect

 This will indicate the proportion of missing values and the numbers of them for each variable in the dataset.

## Range checks (with the tab command)

- use file1, clear
- tab gender

respondent	Freq.	Percent	Cum.
male female	3	50.00 50.00	50.00 100.00
Total	6	100.00	

# Graphical consistency checks with a matrix plot

. graph matrix mpg weight length displacement



## Consistency checks with pwcorr (pairwise Pearson correlations)

pwcorr educ	income, sig	obs
	educ	income
educ	1.0000	
	6	
income	0.8685	1.0000
	6	6

# Consistency checks with listwise correlate command

. webuse auto (1978 Automobile Data)

. correlate mpg weight (obs=74)

	mpg	weight
mpg weight	1.0000 -0.8072	1.0000

### Problems with bivariate correlations

- They are dependent on the levels of measurement of the variables to which they are applied.
- They do not detect nonlinear correlations.
- They do not detect influence of intervening variables.
- They do not detect the influence of antecedent variables.
- "All the world is multivariate (Edward Tufte)"
- They are not sufficient statistics. They are not adequate for an analysis.

### Variable construction

 Subset(conditional) if is used to qualify commands: summarize if _n < 100, detail</li>
 Generate is used to create new variables generate newvar=oldvar + 1 generate dummy=0 if oldvar ~=.

# Variable construction and transformation

- Replace is used to recode existing variables replace newvar = -9 if newva r==. replace dummy = 1 if oldvar < 12 & oldvar ~=.</li>
- 2. Egen command is used to construct variables across the rows of the dataset. egen rownmis = rownonmissing(var1,var2,var3) egen meanr= rowmean(var2,var4,var7) egen maxr=rowmax(var4-var6) egen sdr = rowsd(var5-var9) egen rowtot = rowtotal(var1,var2,var3)

# Variable construction and transformation

Observation numbering with _n and _N

## Indexing date – time variables for time series analysis

 You can index a dataset by time and construct a date (time) variable in order to perform time series analysis.



### **Time variable formats**

- . gen month = m(1987m1) + time-1
- . format month %tm
- list if _n < 10

	time	У	month
1.	1	9.5818075	1987m1
2.	2	11.63626	1987m2
3.	3	13.67958	1987m3
4.	4	12.388329	1987m4
5.	5	13.531665	1987m5
6.	6	12.733157	1987m6
7.	7	15.242382	1987m7
8.	8	13.214064	1987m8
9.	9	15.018662	1987m9

- . gen qtr = q(1987q1) + time 1
- . format qtr %tq
- . list if _n < 10

	time	у	month	qtr
1.	1	9.5818075	1987m1	1987q1
2.	2	11.63626	1987m2	1987q2
3.	3	13.67958	1987m3	1987q3
4.	4	12.388329	1987m4	1987q4
5.	5	13.531665	1987m5	1988q1
6.	6	12.733157	1987m6	1988q2
7.	7	15.242382	1987m7	1988q3
8.	8	13.214064	1987m8	1988q4
9.	9	15.018662	1987m9	1989q1

### More time variable formats

gen week= w(1987w1)+time-1

format week %tw

list time y week if  $_n < 10$ 

	time	У	week
ι.	1	9.5818075	1987w1
2.	2	11.63626	1987w2
3.	3	13.67958	1987w3
4.	4	12.388329	1987w4
5.	5	13.531665	<b>1987w</b> 5
5.	6	12.733157	1987w6
7.	7	15.242382	1987w7
8.	8	13.214064	1987w8
9.	9	15.018662	1987w9

gen year = y(1987) + time - 1

format year %ty

. list time y year if _n < 10

	time	У	year
1.	1	9.5818075	1987
2.	2	11.63626	1988
3.	3	13.67958	1989
4.	4	12.388329	1990
5.	5	13.531665	1991
6.	6	12.733157	1992
7.	7	15.242382	1993
8.	8	13.214064	1994
9.	9	15.018662	1995

### **Time variables**

#### gen day = d(02jan1987) + time - 1

. format day %td

list time y day if _n < 10

	time	У	day
1.	1	9.5818075	02jan1987
2.	2	11.63626	03 jan 1987
3.	3	13.67958	04 jan 1987
4.	4	12.388329	05 jan 1987
5.	5	13.531665	06jan1987
6.	6	12.733157	07 jan 1987
7.	7	15.242382	08jan1987
8.	8	13.214064	09 jan 1987
9.	9	15.018662	10jan1987

#### 📋 crisisTime.do

```
* Construction of Crisis Day time variable
gen day1 = d(190ct1987)
gen newtime = dhms(day1,hours,minutes,seconds)
format newtime %tc
list day1 hours minutes seconds newtime if _n < 11</pre>
```

. list day1 hours minutes seconds newtime if _n < 11

	day1	hours	minutes	seconds	newtime
1. 2. 3. 4. 5.	19oct1987 19oct1987 19oct1987 19oct1987 19oct1987 19oct1987	8 8 9 9	15 30 45 0 15	0 0 0 0	19oct1987 08:15:00 19oct1987 08:30:00 19oct1987 08:45:00 19oct1987 09:00:00 19oct1987 09:15:00
6. 7. 8. 9. 10.	19oct1987 19oct1987 19oct1987 19oct1987 19oct1987	9 9 10 10 10	30 45 0 15 30	0 0 0 0	19oct1987 09:30:00 19oct1987 09:45:00 19oct1987 10:00:00 19oct1987 10:15:00 19oct1987 10:30:00

### Indexing the observations by time

- After the time variable is formatted,
- Type: tsset 'name of time variable' (tip: don't use the quotes)
- Then type: tsline 'name of variable to analyze'
- Add a title to the graph
- tsline gdp, title(time plot of GDP)

### **Indexing Panel datasets**

#### list

	company	time	score	age	gender
1. 2. 3. 4. 5.	1 1 2 2	1 2 3 1 2	10 14 18 11 17	20 20 20 21 21	m m f f
6. 7. 8. 9. 10.	2 3 3 4	3 1 2 3 1	21 14 15 16 17	21 20 20 20 19	f m m f
11. 12. 13. 14. 15.	4 4 5 5 5	2 3 1 2 3	19 15 20 23	19 19 20 20 20	f f m m

do "C:\DOCUME~1\DRROBE~1.YAF\LOCALS~1\Temp\STD16000000.tmp"

tsset company time
 panel variable: company (strongly balanced)
 time variable: time, 1 to 3 delta: 1 unit

Ĩ	l St	tata	Do-l	ile	Edit	or -	Unt	itle	d1.d	0
Ē	<u>F</u> ile	E	dit	<u>S</u> ear	ch	<u>T</u> ool	s			
		Ð		٢	•	X	þ	ß	r	T
	<u> </u>	Untit	led1	.do						
Γ	ts	set	cor	npar	ny t	tim	e			
			-							

### Loop programming

- For recodes
- For aggregation
- For simulation

## The forvalues loop for looping over consecutive values

```
. forvalues i = 1(2)10{

2. display "i = ",`i'," i^2 = ",`i'^2

3. }

i = 1 i^2 = 1

i = 3 i^2 = 9

i = 5 i^2 = 25

i = 7 i^2 = 49

i = 9 i^2 = 81
. forvalues j= 10(-2)1 {
   2. display "j = ",`j',"j^3 = ",`j'^3
   3. }
j = 10 j^3 = 1000
j = 8 j^3 = 512
j = 6 j^3 = 216
j = 4 j^3 = 64
j = 2 j^3 = 8
```

### The foreach loop



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<u>Eile Edit S</u> earch <u>T</u> ools
□ Untitled2.do
<pre>* We can use foreach for selective searches list foreach var of varlist b-v1 {    list `var' if `var' &lt; 4 }</pre>
line number: 9

### The foreach Loop

£40 -	_													_					1.1
	<u> </u>	Stat	a Do	File	Edit	ior -	Ur	titl	e∢∙						3				1 and the second se
	Eil	e	<u>E</u> dit	<u>S</u> ea	rch	<u>T</u> ool	s								÷.				
		E				22		G	5	2	2	<b>P</b>	5	1			Lc	oop.o	dta
	(iii)	Unt	titled	1.do									⊲	⊳ >	<				
	<pre>local varlist "b c v1 v2 v3" foreach var in `varlist' {   recode `var' (8=2)(9=.)   }</pre>																		
C t	Conv he l	vert eft.	s the	e da	ta se	et or	n tł	ne r	igh [.]	t to	th	at c	on						A LEADER
id	b	с	<b>v1</b>	<b>v</b> 2	v3	]			ST-	2					id	b	c	<b>v1</b>	V2
1 2 3 4 5	3 5 7 8 3	8 4 1 3 1	3 1 8 2 3	9 2 4 1 9	4 3 3 3 3			Σ		-^ ~				1. 2. 3. 4. 5.	1 2 3 4 5	3 5 7 2 3	2 4 1 3 1	3 1 2 2 3	24

1. 2. 3. 4.

5.

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v2

.

v3

43333

# conditional statistics: statistics by groups

	. tab foreign	1					
3	Car type	Freq.	Percent	Cum.			
A Designation	Domestic Foreign	52 22	70.27 29.73	70.27 100.00			
	Total	74	100.00				
	. sort foreig	ın					
11000	. bysort fore	ign: summariz	e price mpg	weight			
1000	-> foreign =	Domestic					
	Variable	Obs	Mean	Std. Dev.	Min	Max	
A DESCRIPTION OF THE PARTY OF T	price mpg weight	52 52 52	6072.423 19.82692 3317.115	3097.104 4.743297 695.3637	3291 12 1800	15906 34 4840	
1011	-> foreign =	Foreign					
	Variable	obs	Mean	Std. Dev.	Min	Max	
A DESCRIPTION	price mpg weight	22 22 22	6384.682 24.77273 2315.909	2621.915 6.611187 433.0035	3748 14 1760	12990 41 3420	

# Collapse command for aggregating datasets

. collapse (mean) mpg, by(foreign rep78)

. list

	гер78	foreign	mpg
1.	1	Domestic	21
2.	2	Domestic	19.125
3.	3	Domestic	19
4.	4	Domestic	18.4444
5.	5	Domestic	32
6.		Domestic	23.25
7.	3	Foreign	23.3333
8.	4	Foreign	24.8889
9.	5	Foreign	26.3333
10.	-	Foreign	14

# Expand for elaboration by a subdivision

	area	blocks	
1. 2. 3. 4. 5.	1 2 3 4 5	2 3 1 5 3	
. expa (9 obs . list	and bloc servatio	cks ons create	≥d)
	area	blocks	
1. 2. 3. 4. 5.	1 2 3 4 5	2 3 1 5 3	
6. 7. 8. 9. 10.	1 2 2 4 4	2 3 5 5	
11. 12. 13. 14.	4 4 5 5	5 5 3 3	



sort area blocks

list

	area	blocks
1.	1	2
2.	1	2
3.	2	3
4.	2	3
5.	2	3
6.	3	1
7.	4	5
8.	4	5
9.	4	5
LO.	4	5
L1.	4	5
L2.	5	3
L3.	5	3
L4.	5	3

## Simulation of distributions



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## The Father of the Gaussian Distribution

**Carl Friedrich Gauss** 



Johann Carl Friedrich Gauss (1777–1855), painted by Christian Albrecht Jensen

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# Normal Distribution Gaussian Distribution per C. F. Gauss)



### **Monte Carlo Simulations**

Stata Do-File Editor - simRegModel.do File Edit Search Tools 🗋 💀 📾 🖨 🥻 🐰 🕛 🛍 🖝 🕤 💭 🗍 📋 simRegModel.do 📋 Untitled3.do clear capture program drop het3 drop all set obs 100 set seed 1234 gen x = invnormal(uniform()) * We set up the true value of b = 2 gen true y=1 + 2*x save truth, replace set more off program het3 version 10.1 args true y x b capture drop y gen y=true y + (invnormal(uniform())+ `b'*x) regress y x end * we will set the value of b to equal 2+ 2 more=4 simulate b se, reps(10000): het3 true y x 0 summarize b x- se cons

### Exercises 2

- 1. Construct two toy datasets, and merge them by a common id variable.
- 2. Concatenate those two datasets.
- 3. Download a dataset from ucla.ats from yahoo
- 4. Convert the dataset to a Stata dataset
- 5. Graph the series
- Using the loop.dta dataset and a foreach loop in Stata, convert all values > 7 to missing

### **Exercises 2**

- 7. Construct a log of your work and then
- 8. Convert the blood pressure dataset, bpwide.dta to a long dataset
- 9. Convert the wide dataset to a long one,
  10.Close the log file
  11.Convert the smcl file to a txt file
  12.Reshape the reshapeW.dta file to a reshape long form.
### Exercises 2

- 12. Use the dataset auto1.dta. Obtain the means of the mpg and weight by foreign to obtain aggregate statistics.
- 13. Plot a histogram of the mpg variable.
- 14. List the extreme values of that variable.
- 15. What is the mode of the mpg of all the cars in the dataset? What is the mean? What is the range?
- 16. Construct a table of means by car type (foreign).
- 17. What is the Pearson correlation between mpg and weight?
- 18. What is the correlation between mpg and foreign?
- 19. Is the relationship between repair record 1978 and car type significant? What is the Gamma correlation of that relationship?
- 20. How do we show whether this relationship is statistically significant?

### Statistical and project planning

#### Size matters

- Power and sample size analysis: A priori versus
- Post-hoc.
- Sampling planning
  - Probability sampling, clinical trials, and other respectable methods of data collection
  - Stata is wonderful for complex samples
- Respondent protection
  - Informed consent
  - Confidentiality
  - Anonymity
  - Protection of health related information by law
- Pilot studies
  - Proper size
  - Control groups
  - Random selection and random assignment
  - Matching
- Data security
  - Storage
  - Off-site storage
  - Masking of id
- Longitudinal analysis
  - TIME SERIES DATA
  - PANEL DATA
  - SPATIAL DATA
  - For longitudinal studies, censoring and sample attrition must be estimated and planned for. Comparison of pretest scores.

#### Power and sample size analysis

- Conventional statistics are asymptotic. They work when the same size becomes large (and often do not work with smaller samples).
- The question becomes how large a sample is large enough?
- Power and sample size analyses usually indicate the sufficiency of the sample size.
- To properly plan a research project, we must determine how many subjects or respondents we must interview or question.

## Statistical Power Analysis for the Behavioral Sciences (1988) was at NYU



#### Jacob Cohen, PhD

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#### **Power analysis**

- There are 3 types of errors that can be made. The type 1 error is rejecting a true null hypothesis. The probability of this type of error is called alpha, α. This is a false negative.
- The type 2 error is accepting a null hypothesis when it is false and should be rejected. The probability of this type of error is called beta,β, and is not to be confused with a standardized regression coefficient, also called beta.

### Type 3 errors

 Not asking the correct question in the first place ⁽²⁾

# What significance level should be used?

- The level of significance to be used depends on the consequences of making a mistake.
- For social sciences, alphas of .05 are generally used by convention. A scholar's reputation may be at stake here.
- For medical and toxicological studies, much more stringent standards are required because the consequences of making a mistake may be lifethreatening. Alphas of 0.01 to 0.001 are often used in these cases.

### **Power and Sample size analysis**

- The power of a statistical test is defined as  $1 \beta$ .
- The power to reject a false positive depends on the ability to detect an effect of that size.
- Jacob Cohen (1988) Statistical Power Analysis for the Behavioral Sciences, Lawrence Erlbaum Associates: Hillsdale, NJ has formulated conventional (small, medium, and large) effect sizes for basic statistical tests.

# Tables given the n needed are supplied.

The conventional standard is that the project director should enough respondents or subjects to have a sample large enough to detect a medium or small effect size with a power of at least 0.80.

If performing a t-test, small, medium, and large effect sizes are d=2.,.5,.8., where d = (m1-m2)/(stdev)

### Cohen's effect sizes

1	Statistical	test		effect		two-tailed	tests		
2						small	medium	large	
3	t test for m	leans							
4	case 3:	one sample		d	(m=c)/sd	0.2	0.5	0.8	
5	case 1:	ind samples	diff n	d	(m1-m2)/sd	0.2	0.5	0.8	
6	case 2:	ind samples	diff sd	d	(m1-m2)/sd	0.2	0.5	0.8	
7	case 4:	paired samp	les	d	(m1-m2)/sd	0.2	0.5	0.8	
8									
9	Pearson correlation		r		0.1	0.3	0.5		
10									
11	11 Differences between correlations			q	z1-z2	0.1	0.3	0.5	
12	case 0:	equal sampl	e sizes		where				
13	case 1: different sample sizes			z=.5 ln((1+r)/(1-	r))				
14	case 2:	one sample							
45									

### Cohen's effect sizes

Book1									
	A	В	С	D	E	F	G	Н	1
16	Differences	s between	proportions	h	phi1-phi2				
17					phi=2arcsin(sqr	t(P))			
18	case 0:	equal sam	ple sizes			0.2	0.5	0.8	
19	case 1:	different n				0.2	0.5	0.8	
20	case 2:	one sampl	e			0.2	0.5	0.8	
21									
22	Chi-square	etest		w	Sqrt(chi-sq)				
23	case 0:	goodness	of fit			0.1	0.3	0.5	
24	case 1:	contingend	cy table			0.1	0.3	0.5	
25									
26	ANOVAS			f	1/sqrt(ICC)				
27	case 0	one-way a	nova eq n			0.1	0.25	0.4	
28	case 1	one-way a	nova uneq n			0.1	0.25	0.4	
29	case 2	main effect	ts in factorial or complex design			0.1	0.25	0.4	
30	case 3	interaction	s in factorial designs			0.1	0.25	0.4	
31									
32	32 Regressions			f^2	eta^2/(1-eta^2)	r^2=.02	r^2=.13	r^2=.538	
33	case 0	multiple re	gression with u predictors		=(ICC)/(1-ICC)	0.02	0.15	0.35	
34	case 1	model 1 er	ror for hierarchical regression		=R^/2(1-R^2)	0.02	0.15	0.35	
35	case 2	uniquely te	esting a set of c vars model 2 err	or	=1 - ess/tss	0.02	0.15	0.35	
36									
37									

# Stata can compute post-hoc power and sample size

#### For t-tests and proportions

0.0500 (two-sided) alpha = 0.8000 power = m1 =.8 m2 = .5 sd1 = .6 sd2 = .9 n2/n1 =1.00 Estimated required sample sizes: n1 = 103  $n^{2} =$ 103

For repeated measures contrasts For survival analysis problems

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# Attrition is to be compensated for in the planning of the sample size.

- A pilot study will indicate the rate of attrition if it is representatively sampled and collected.
- If there is five percent attrition, then 105% of the sample size should be collected. Sample size = Number to be collected/.95 = 211 (rounded to nearest integer)
- If the margin of error is 5 more %, then 110% of the needed sample size should be collected for the larger sample. Sample size to be collected = 211/.95 = 223 (rounded to nearest integer).
- If the pilot study indicates that 10 percent of the items will on the average not be answered for those who remain in the study, then add another 10% to the 110% of the needed sample size that must be collected. 120% of the needed sample size must be obtained in the planning stage. Sample size to be collected = 223/.90 = 248.
- If you are studying a hard to reach minority, increase your safety margin. If you
  are conducting a longitudinal study in an area that is politically unstable, be
  careful, focus on your primary objective and avoid unnecessary entanglements or
  distractions.

# Attrition and censoring in longitudinal studies

- Attrition is accounted for by censoring. There is right censoring when a person is lost to followup.
- There is right censoring when the event has not occurred prior to the end of the study.
- There is interval censoring when the patient is in jail for 2 weeks and cannot attend his midterm interview.

### Sample size reduction

- Bubble sheets cannot always be read clearly if the survey is on both sides of the paper. Machines make many mistakes in scanning such sheets.
- Bubble sheets cannot always be read clearly if the answers are not closed ended. Avoid open-ended questions
- Transmission over the web must be double checked to be sure that there was not information corruption in transmission of data.
- Do not allow people not to answer if the answer is negative. This breeds confusion and uncertainty.

# Indexing survival-time data for bio-statistical analysis

. webuse drugtr, clear (Patient Survival in Drug Trial)								
. stset studytime, failure(died)								
failure event: <b>died != 0 &amp; died &lt; .</b> obs. time interval: <b>(O, studytime]</b> exit on or before: <b>failure</b>								
48 total obs. 0 exclusions								
<pre>48 obs. remaining, representing 31 failures in single record/single failure data 744 total analysis time at risk, at risk from t = 0 earliest observed entry t = 0 last observed exit t = 39</pre>								
. stdes								
failure _d: analysis time _t:	died studytime							
			— per _. subj	ect	———————————————————————————————————————			
Category	total	mean	min	median	max			
no. of subjects no. of records	48 48	1	1	1	1			
(first) entry time (final) exit time		0 15.5	0 1	0 12.5	0 39			
subjects with gap time on gap if gap time at risk	0 0 744	15.5	1	12.5	39			
failures	31	. 6458333	0	1	1			

### Indexing survival time data for prostate cancer

webuse catheter, clear (Kidney data, McGilchrist and Aisbett, Biometrics, 1991)

stset time infect

failure event: infect != 0 & infect < .
bbs. time interval: (0, time]
exit on or before: failure</pre>

76 total obs.
0 exclusions

76 obs. remaining, representing
58 failures in single record/single failure data
7424 total analysis time at risk, at risk from t = 0
earliest observed entry t = 0
last observed exit t = 562

# Kaplan Meier Survival curves by gender adjusted for age



## Visualization for exploratory data analysis and model diagnosis

- 1-dimensional Univariate
  - Histograms
  - Box plots
  - Stem and leaf plots
  - Quantile plots
  - Bar graphs
  - Pie charts
- 2-dimensional Scatterplot matrices
  - Scatterplots
  - Time series plots
- Multi-dimensional plots
  - Panel plots
  - 3-D scatterplots
- Graphics editor

## Exploratory Data Analysis Edward Tufte (Princeton Univ)



# Matrix scatterplots for exploring functional form of relationships

	10 20 30 40				2,000 3,000 4,000 5,0		30 40 50	2	.00 2.00 4.0	•
Price					an a	and the second				
40	Mileage , (mpg)									
		Repair Record 1978			· · · ·			· · · · · · · · · · · · · · · · · · ·		
			Headroom (In.)		un un fréderic Fréderic					
				Trunk space (cu. ft.)	an sharin			ない		
					Weight (ibs.)	and the state of the		A.C.		
					and the second second	Length (In.)			动动	
						and a state	Tum Circle (ft.)		A line away	
seen and a second s	n de la composition de la comp			and and a second se Second second s	المربعين المربعين مربع		ander -	Displacement (cu. in.)	all and an and a second	
	an aide a tha a Talais a bha Talais								Gear Ratio	ļ
·										Car type

graph matrix mpg-foreign Alan Yaffee, Ph.D.

#### **Exploratory data analysis**

sort foreign graph box mpg, over(foreign) title(Comparison of box plots)



#### Horizontal bar charts



#### Nesting horizontal bar charts

graph hbar price, over(foreign) over(rep78) title(Number of repairs needed in 1978) ///
subtitle(for average price of car in 1978 US dollars) blabel(bar) ///
ytitle("Average price of car") bar(1,bcolor(sand)) asyvars



#### **Pie Charts**



. graph pie price. over(foreign) title(Relative Prices of Foreign and Domestic Cars) plabel( all percent.color(white))

### **Comparative histograms**

histogram mpg, discrete by(foreign) normal title(Comparative histograms)



#### **Comparative stem and leaf plots**

#### Results

. by foreign: stem mpg

-> foreign = Domestic

Stem-and-leaf plot for mpg (Mileage (mpg))

1t	22
<b>1f</b>	4444455
1s	666677
1.	88888889999999999
2*	000111
2t	22222
2f	4445
2s	66
2.	889
3*	0
3t	
3f	4

-> foreign = Foreign

Stem-and-leaf plot for mpg (Mileage (mpg))

1* 4 1. 788 2* 113334 2. 555568 3* 01 3. 55 4* 1

# The relationship between fuel economy and luxury in auto purchases



# Comparison of mpg per price between foreign and domestic cars



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# Nonlinear fit between mpg and price



. graph twoway scatter mpg price || qfit mpg price, title(Cheaper cars get better gas mileage) > subtitle(Why the auto industry is in difficulty) ytitle(mpg)

### Identifying the most and least expensive cars

. extremes price make,

obs:	price	make
1.	3,291	Merc. Zephyr
2.	3,299	Chev. Chevette
3.	3,667	Chev. Monza
4.	3,748	Toyota Corolla
5.	3,798	Subaru

69.	12,990	Peugeot 604
70.	13,466	Linc. Versailles
71.	13, 594	Linc. Mark V
72.	14,500	Cad. Eldorado
73.	15,906	Cad. Seville

Command

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### Paneled graphs



. graph twoway scatter lexp safewater || qfit lexp safewater, by(region) title( Life Expectanc > y by safewater)

### Fit and confidence intervals



. graph twoway scatter lexp safewater || qfitci lexp safewater, by(region) title( Life Expecta > ncy by safewater)

# Time series plot of life expectancy by gender



# Life expectancy by sex and race over time



### **Survival Analysis**


# Dot plot of public and private education by country

🔟 Stata Graph - Graph 🛛 🚺 🖬 🗖 🔀
Eile Edit Object Graph Tools Help
Graph 🛛 🕹 🗙
Proportions of public and private education
Australia
Britain
Canada
Denmark
France
Germany
Ireland
Netherlands
Sweden
United States
0 .5 1 1.5
mean of public  mean of private

. graph dot public private, over(country) title(Proportions of public and private educ > ation)

## How much air conditioning is needed on average in the U.S. each year?



graph bar (mean) cooldd, over(division) title(How much cooling is needed on average in the U.S.) asyvars

### Saving and Exporting graphs

### You can save a Stata graph with the command: graph save ch1fig1.gph

The gph suffix indicates that it is a Stata graph.

If you wish to resave this graph later, attach the replace option after the graph name.

You can export a Stata graph with the command: graph export ch1fig1.wmf, replace graph export ch1fig1.emf, replace graph export ch1fig1.eps, replace graph export.ch1fig1.tif graph export.ch1fig1.pdf

### **Distributional analysis**

- Simulation with random number generators of normal, poisson, chi square, binomial, gamma, hypergeometric, and other distributions
- Kernel density plots (distributional structure)
- Histograms (with superimposed normal curves)
- Lowess plots (linearity and functional form)
- Quantile plots
- Stem and leaf plots

### Kernel density plots

f

### Nonparametric density plots



$$_{ernel}(x) = \frac{1}{nh_j} \sum_{i=1}^n K_j\left(\frac{(x_{ij} - x_j)}{h_j}\right)$$

where  $f(.) = kernel \ density \ estimator$   $K = kernel \ function \ symmetrically \ weights \ observations$  $h_j = bandwidth \ for \ local \ smoothing \ of \ data$ 

### Some Kernel functions

**Some Kernel Smoothers** 



### Quantile normal plots



### 3d Graphs can be generated with some user effort



### Item and Scale analysis

- Scale construction
- Alpha reliability
- Kappa reliability
- ICC23 reliability is also possible but will not be shown here. You have to download icc23 from the ssc archive.

### Exercises 3

- 1. Plot a matrix scatterplot of headroom to weight in the dataset auto1.dta
- 2. Plot a lowess graph between mpg and weight
- 3. Use a horizontal bar chart to show the mpg of foreign and domestic cars. Put a main and axis titles in it. Put in a note or caption describing it.
- 4. Generate a stem-leaf plot of weight by foreign.
- 5. Generate a dot plot of make by mpg.
- 6. Generate a kernel density plot of mpg.
- 7. Generate a time plot of GDP downloaded from FRED.
- 8. Generate an overlay time plot of CPI and GDP over the same range of time, downloading both from FRED.

## Cronbach Alpha reliability (internal consistency of scale items)

hissants							
. alpha price rep78 headroom trunk weight length turn displ, std item detail							
Test scale = r	mean(standardi	zed items)			lr Ir	ncorrect codin <mark>s</mark>	
						hacolina	
		item-test	item-rest	average inter-item		Daseime	
Item	Obs Sign	correlation	correlation	correlation	alpha		
price	70 + /	0, 5260	0.3719	0, 5993	0.9128		
ren78	61 - <	0.4874	0.3398	0.6040	0.9143		
headroom	66 +	0.6716	0. 5497	0.5542	0.8969		
trunk	69 +	0.7979	0.7144	0.5159	0.8818		
weight	64 +	0.9404	0.9096	0.4747	0.8635		
length	69 +	0.9382	0.9076	0.4725	0.8625		
turn	66 +	0.8678	0.8071	0.4948	0.8727		
displacement	63 +	0.8992	0.8496	0.4852	0.8684		
Test scale				0.5251	0.8984		
Interitem corr	relations (rev	erse applied)	(obs=pairwise, s	see below)			
	price	rep78	headroom	trunk	weight	length	
price	1.0000						
rep78	-0.0479	1.0000					
headroom	0.11/4	0.1955	1.0000				
trunk	0.2/48	0.2///	0.6841	1.0000	1 0000	10	
weight	0.5093	0.3624	0.5464	0.6486	1.0000	1 0000	
Tength	0.4511	0.3162	0.5823	0.7404	0.9425	1.0000	
turn	0.3528	0.4/15	0.406/	0.5900	0.8/12	0.8389	
arspracement	0.003/	0.3391	0. 2100	0.04/1	0.8/33	0.8422	
	turn	displacement					
turn	1.0000						
displacement	0.7723	1.0000					

### Do we reverse code?

- If (-0.20 <= correlation => .20), we can reverse code if this improves scale alpha.
- Otherwise, we delete the item.
- We iterate until scale alpha is greater than 0.70. If scale alpha < 0.70, we use individual items instead of scale.



## Cohen's Kappa Reliability

- Kappa reliability is a form of interrater agreement that is evidence of independent corroboration of concurrence of interpretation. The higher this agreement, the more there appears to be a consensus about the meaning of the object of evaluation.
- Kappa is designed to correct for chance agreement.

### Cohen's kappa (1960) for two raters classifying n items into C categories

 The denominator in the ratio corrects for chance agreement

 $\kappa_{Cohen} = \frac{Pr(observed \ agreement) - Pr(expected \ [by \ chance] agreement)}{1 - Pr(expected \ [by \ chance] \ agreement)}$ 

0 = no agreement 0-.20 very low agreement .21-.40 low agreement .41-.60 moderate agreement .61-.8 full agreement .81-1.00 almost perfect agreement

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# Joe Fleiss (Columbia ) and Jack Cohen (NYU) came up with the weighted kappa

Joseph L. Fleiss



Fleiss developed the modern Intra-Class correlation coefficient with Pat Shrout ( formerly of Columbia and now at NYU)



 Fleiss and Cohen(1973), "The Equivalence of the weighted Kappa and the intraclass correlation coefficient as measures of reliability" in Educational and Psychological Measurement, Vol. 33, pp. 257-268 wrote that the weighted Kappa was equivalent to the intraclass correlation coefficient as a measure of reliability.

### Fleiss's Kappa (1981)

### Joe Fleiss's kappa

$$\kappa_{Fleiss} = \frac{\overline{P} - \overline{P}_e}{1 - \overline{P}_e}$$

### where

the numerator accounts for actual agreement above chance, the denominator accounts for extent of possible agreement above chance.

# Intra-class correlation Coefficient as a measure of reliability Winer, Brown, and Michaels (1991)

Statistical Principles of Experimental Design, McGraw Hill: New York, 127-129.

 If the model is a two-way ANOVA layout, are the judges fixed or random? The targets are deemed random. If the judges are fixed, the model is a two-way mixed effects ANOVA. If they are random, the model is a two-way random (randomized block design) effects ANOVA. Another effect to be controlled for is he error variance.

Types of Intra-class correlation = Cohen's multi-rater kappa: When treatments are random:

 $ICC(consistency) = \frac{Variance(rating) - variance(residual)}{[Variance(rating) - Avg(variance(resid)] + Variance(ratings) - Avg[variance(resid)]}$  $ICC(absolute agreement) = \frac{[Variance(rating of targets) - (variance(error)]]}{Variance(error) + Average(Variance(rating of targets) - average(Variance(error)))}$  $If targets are fixed, ICC = \omega^{2}(omega - squared)$ 

### Intra-class correlation in a nutshell

- It is the proportion of agreement to the total amount of variation (from agreement, disagreement, possible interaction, and error).
- There are more than 5 ways of computing this ICC.

### For fixed treatments $\omega^2$

Stata can compute omega squared:

$$\omega^{2} = \frac{\frac{\sum \tau_{j}^{2}}{k}}{\left(\frac{\sum \tau_{j}^{2}}{k} + \sigma_{e}^{2}\right)}$$

= proportion of population variance accounted for by agreement

where

k = number of treatment groups or rating categories  $\tau_j^2 = Sum$  of squares of treatment or ratings  $\sigma_e^2 = error$  variance

### Kappa reliability

#### Corrects for chance and applicable with multiple raters. •

. webuse rat (Altman p. 4	e2, clear 03)					
. describe						
Contains dat obs: vars: size:	a from http 85 4 1,530 (9	<b>p://www.stat</b> 99.9% of mem	a-press.com	/data/r10/ra Altman p. 4 3 Mar 2007	te2.dta 03 21:50	
variable nam	storage le type	display format	value label	variable la	bel	
rada radb pop group	byte byte long float	%8.0g %8.0g %10.0g %9.0g	diag diag	Radiologist Radiologist _n	A's assessmen B's assessmen	t
Sorted by: . kap rada r Radiologis t A's	adb, tab	adiologist B	's assessme	nt	Total	
Normal benign suspect cancer	21 4 3 0	12 17 9 0	0 1 15 0	0 0 2 1	33 22 29 1	
Total	28	38	16	3	85	
Agreement	Expected Agreement	Карра	Std. Err.	z	Prob>Z	
63.53%	30.82%	0.4728	0.0694	<b>6.81</b>	0.0000	

## Multi-rater kappa к

. describe						
Contains data obs: vars: size:	from <b>p612.d</b> 25 4 700 (99.	ta 9% of memory fi	<b>18 мау 2009 02:51</b> ree)			
variable name	storage di type fo	splay valu rmat labe	e 21 variable label			
subject raters pos neg	float %9 float %9 float %9 double %1	.0g .0g .0g 0.0g	number of raters with positive evaluations number of raters with negative evaluations			
Sorted by: Note: d	Sorted by: Note: dataset has changed since last saved					
. tab raters						
raters	Freq.	Percent	Cum.			
2 3 4 5	7 8 7 3	28.00 32.00 28.00 12.00	28.00 60.00 88.00 100.00			
Total	25	100.00				
. kappa pos n	eg					
Two-outcomes,	multiple ra	ters:				
Карр	a Z	Prob>Z				
0. 541	5 5.28	0.0000				

## Multi-rater multi-category fixed number of raters kappa

. describe				
Contains data from obs: vars: size: <b>2</b>	<b>p615.dta</b> 10 4 40 (99.9% of r	nemory free)	18 May 2009 02:59	
stor variable name ty	age display pe format	value label	variable label	
subjectflcat1flcat2flcat3fl	oat %9.0g oat %9.0g oat %9.0g oat %9.0g			
Sorted by:				
. kappa cat1 cat2	cat3			1
Outcome	Карра	Z	Prob>Z	
cat1 cat2 cat3	0.2917 0.6711 0.3490	2.92 6.71 3.49	0.0018 0.0000 0.0002	
combined	0.4179	5.83	0.0000	

# There are IntraClass Correlations available (types 2 and 3)

- Download from SSC archive
- ssc install icc23

# Summary statistics including measure of central tendency.

- Summarize mean range, std deviation
- Summarize, detail
- Tabstat
- Means
- Group or aggregation statistics with statsby

### Enligtenment in a taxi!

- Hardy, Godfrey H. (1877 1947)
- [On Ramanujan]

I remember once going to see him when he was lying ill at Putney. I had ridden in taxi cab number 1729 and remarked that the number seemed to me rather a dull one, and that I hoped it was not an unfavorable omen. "No," he replied, "it is a very interesting number; it is the smallest number expressible as the sum of two cubes in two different ways." *Ramanujan*, London: Cambridge University Press, 1940.

### Variable transformations

- To transform or not to transform
  - When to
  - When not to
- Retransformation
- Normalizing transformations
- Variance stabilizing transformations
- To log or not to log
  - Naturally
  - By another base

### Henri Poincare 1854-1912

 Later mathematicians will regard set theory as a disease from which one has recovered.



### Summary univariate statistics

. summa	arize mpg we	eight				
Var	iable	obs	Mean	Std. Dev.	Min	Мах
v	mpg veight	74 74	21.2973 3019.459	5.785503 777.1936	12 1760	41 484(
. summa	arize mpg we	eight, det	tail			
		Mil	leage (mpg)			
F	vercentiles	Sma	llest			
5%	14		12			
10%	14		14	obs	74	
25%	18		14	Sum of Wgt.	74	
50%	20			Mean	21.2973	
7.50/	25	Lar	gest	Std. Dev.	5.785503	
7 5%	20		34	Vanianco	22 47205	
95%	34		35	Skewness	9487176	
99%	41		41	Kurtosis	3.975005	
		We	ight (lbs.)			
F	ercentiles	Sma	llest			
1%	1760		1760			
5%	1830		1800	ohe	74	
25%	2020		1820	Sum of Wat	74	
2 3/0	2240		1050	Sum of wgc.	/4	
50%	3190			Mean	3019.459	
		Lar	rgest	Std. Dev.	777.1936	
75%	3600		4290		<b>CO1030</b> -	
90%	4060		4330	Variance	604029.8	
93%	4290		4/20	Skewness	. 1481104	
53%	4040		4040	KUL LUS IS	2.110403	

### Basic categorical data analysis

- Tabulate Tables and Crosstabulations
  - With labels
  - Without labels
  - Inference with
    - Chi-square  $\chi^2$
    - Likelihood ratio chi-square LR  $\chi^2$
    - Gamma γ
    - Kendalls τ
- Tabstat

## One-way tabulations (Frequencies analysis)

. tab age			
age of I			
mother	Freq.	Percent	Cum.
14	3	1.59	1.59
15	3 7	1.59	3.1/
17	12	5.70	12 22
18	10	5 20	18 52
10	16	8 47	26.98
20	18	9.52	36.51
21	12	6.35	42.86
22	13	6.88	49.74
23	13	6.88	56.61
24	13	6.88	63.49
25	15	7.94	71.43
26	8	4.23	75.66
27	3	1.59	77.25
28	9	4.76	82.01
29	7	3.70	85.71
30	7	3.70	89.42
31	5	2.65	92.06
32	6	3.17	95.24
33	3	1.59	96.83
34	1	0.53	9/.33
30	2	1.00	98.41
45	2	0.52	100 00
47		0.33	100.00
Total	189	100.00	
. tab race			
race	Freq.	Percent	Cum.
white	96	50,79	50,79
black	26	13.76	64.55
other	67	35.45	100.00

### Multiple response using (dummy indicators) courtesy of Ben Jann ETH

#### . findit drugs.dta

. use drugs, clear (1997 Survey Data on Swiss Drug Addicts)

. mrtab inco1-inco7, include title(Sources of income) width(24)

	Sources of income	Frequency	Percent of responses	Percent of cases
inco1	private support (partner, family, friends)	252	14.85	25.93
inco2	public support (unemployment insurance, social benefits)	565	33.29	58.13
inco3	drug dealing	291	17.15	29.94
inco4	housebreaking, theft, robbery	38	2.24	3.91
inco5	prostitution	56	3.30	5.76
inco6	"mischeln"/begging	125	7.37	12.86
inco7	legal occupation	370	21.80	38.07
	Total	1697	100.00	174.59
Valid Missir	cases: 972 ng cases: 0			

# Multiple response (polytomous categories) courtesy of Ben Jann (ETH)

label define pinc 1 "private (family, friends, partner)" 2 "public(unemployment insur., ssi, charity)" /// 3 "drug dealing" 4 "robbery, theft" 5 "prostitution" 6 "begging" 7 "legal occupation"

label values pinco1-pinco6 pinc

end of do-file

. mrtab pinco1-pinco6, poly response(1/7) include title(Sources of Illegal Income) width(27)

	Sources of Illegal Income	Frequency	Percent of responses	Percent of cases
1	private (family, friends,	252	14.85	25.93
2	public(unemployment insur., ssi, charity)	565	33.29	58.13
3 4	drug dealing robbery, theft	291 38	17.15 2.24	29.94 3.91
5	prostitution begging	56 125	3.30 7.37	5.76 12.86
Ľ	Tegal occupation	3/0	21.80	38.0/
Val Mis	id cases: 972 sing cases: 0	109/	100.00	1/4.39

# Two-way Tabulations with and without labels

Leo Goodman developed much categorical data analysis.

. tab low race						
birthweigh t<2500g	white	race black	other	Total		
0 1	73 23	15 11	42 25	130 59		
Total	96	26	67	189		
. tab low race, nolabel						
birthweigh t<2500g	1	race 2	3	Total		
0 1	73 23	15 11	42 25	130 59		
Total	96	26	67	189		

### **Bivariate tabulation inference**

. tab low race, row col exp all

birthweigh t<2500g	white	race black	other	Total
0	73	15	42	130
	66.0	17.9	46.1	130.0
	56.15	11.54	32.31	100.00
	76.04	57.69	62.69	68.78
1	23	11	25	59
	30.0	8.1	20.9	59.0
	38.98	18.64	42.37	100.00
	23.96	42.31	37.31	31.22
Total	96	26	67	189
	96.0	26.0	67.0	189.0
	50.79	13.76	35.45	100.00
	100.00	100.00	100.00	100.00
P	earson chi2( <b>2</b> )	) = <b>5.0048</b>	Pr = <b>0</b> .	082
likelihood	-ratio chi2(2)	= <b>5.0104</b>	Pr = 0.	082
	Cramér's 🕅	/ = 0.1627		
	gamma	a = 0.2575	ASE = 0.	125
K	endall's ťau-k	= <b>0.1360</b>	ASE = 0.	. 069

### Pearson Chi-square

Named after Karl Pearson

$$\chi^{2} = \sum_{i=1}^{r} \sum_{j=1}^{c} \left( \frac{(o_{ij} - e_{ij})^{2}}{e_{ij}} \right)^{2}$$

 $e_{ij} = \text{expected frequency} = \frac{(row \ total_i \ * \ column \ total_j \ )}{Grand \ total_{ij}}$ 

o_{ij} = observed count in cell of row i and column j

## Multiple Response courtesy of Ben Jann, ETH

#### Missing cases:

mrtab crime1-crime5, include response(2 3) title(victimation) nonames width(18) by(sex) column mtest(bonfer roni)

#### кеу

frequency of responses column percent of cases

49

	Sex of resp	ondent		
victimation	1	2	Total	chi2/p*
hit someone	33 13.20	88 13.11	121 13.14	0.001
use a weapon against someone	8 3.20	15 2.24	23 2.50	0.696 1.000
sexual harassment, rape	26 10.40	0 0.00	26 2.82	71.811 0.000
robbery (including drug theft)	31 12.40	65 9.69	96 10.42	1.430 1.000
blackmail	15 6.00	12 1.79	27 2.93	11.353 0.004
Total	113 45.20	180 26.83	293 31.81	
Cases	250	6/1	921	

* Pearson chi2(1) / Bonferroni adjusted p-values

Valid cases: 921 Missing cases: 49
## **Customized tables**

tabstat price weight mpg rep78, by(foreign) stat(mean median sd min max sk kurtosis) long col(stat)

foreign	variable	mean	p50	sd	min	max	skewness	kurtosis
Domestic	price	6072.423	4782.5	3097.104	3291	15906	1.777939	5.090316
	weight	3317.115	3360	695.3637	1800	4840	24371	2.784673
	mpg	19.82692	19	4.743297	12	34	.7712432	3.441459
	rep78	3.020833	3	.837666	1	5	0388361	3.574874
Foreign	price	6384.682	5759	2621.915	3748	12990	1.215236	3.555178
	weight	2315.909	2180	433.0035	1760	3420	1.056582	3.368013
	mpg	24.77273	24.5	6.611187	14	41	.657329	3.10734
	rep78	4.285714	4	.7171372	3	5	4592793	2.104167
Total	price	6165.257	5006.5	2949.496	3291	15906	1.653434	4.819188
	weight	3019.459	3190	777.1936	1760	4840	.1481164	2.118403
	mpg	21.2973	20	5.785503	12	41	.9487176	3.975005
	rep78	3.405797	3	.9899323	1	5	0570331	2.678086

## Means

. means mpg trunk weight								
Variable	Туре	obs	Mean	[95% Conf.	Interval]			
mpg	Arithmetic	74	21.2973	19.9569	22.63769			
	Geometric	74	20.58444	19.38034	21.86335			
	Harmonic	74	19.92318	18.81185	21.17405			
trunk	Arithmetic	74	13.75676	12.76576	14.74775			
	Geometric	74	13.04276	12.05332	14.11342			
	Harmonic	74	12.27399	11.28267	13.45629			
weight	Arithmetic	74	3019.459	2839.398	3199.521			
	Geometric	74	2918.284	2743.65	3104.034			
	Harmonic	74	2816.578	2649.055	3006.719			

## Comparison of two means

### Parametric t-tests

- Assumptions
  - Observations are i.i.d.
  - Variances may be equal or corrected for nonequality
- One sample
- Two independent sample
- Paired
- Alternative Nonparametric rank tests
  - Man-Whitney U test
  - Wilcoxon signrank

William S. Gosset (a.k.a. Student)

 Worked at Guiness's brewery in Dublin and developed the t tests and t distribution to solve problems he encountered there.



William Sealy Gosset

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## One sample t-test

. ttest mpg=30

One-sample t test

Interval]	[95% Conf.	Std. Dev.	Std. Err.	Mean	Obs	Variable
22.63769	19.9569	5.785503	.6725511	21.2973	74	mpg
= - <b>12.9398</b> = 73	t : of freedom :	degrees			= mean( <b>mpg</b> ) = <b>30</b>	mean = Ho: mean =
ean > <b>30</b> ) = <b>1.0000</b>	Ha: m Pr(T > t)	30 0.0000	Ha: mean != T  >  t ) =	Pr(	ean < <b>30</b> ) = <b>0.0000</b>	Ha: me Pr(T < t)

One sample 
$$t = \frac{\overline{x_{2i}} - \mu_0}{\frac{sd}{\sqrt{n}}}$$
  $df = n - 1$ 

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## Independent samples t-test

Contains c obs: vars: size:	data from h 189 11 4,158	ttp://www.st (99.9% of m	ata-press.co	m/data/r10/lbw.dta Hosmer & Lemeshow data 15 Jan 2007 05:01	
variable r	storag name type	e display format	value label	variable label	
id low age lwt race smoke ptl ht ui ftv bwt	int byte int byte byte byte byte int	%8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g %8.0g	race	identification code birthweight<2500g age of mother weight at last menstrual period race smoked during pregnancy premature labor history (count) has history of hypertension presence, uterine irritability number of visits to physician during 1st trimest birthweight (grams)	er
Sorted by: . ttest lo Two-sample	: ow, by(smok e t test wi	e) th equal var	iances		
Group	obs	Mean	Std. Err.	Std. Dev. [95% Conf. Interval]	
0 1	115 74	.2521739	.0406722	.436161 .1716025 .3327453 .4943217 .2908804 .5199305	
combined	189	. 3121693	.0337954	.4646093 .2455025 .3788361	
diff		1532315	.0685141	28839140180715	
diff = Ho: diff =	= mean( <b>0</b> ) - = 0	mean( <b>1</b> )		t = -2.2365 degrees of freedom = 187	
Ha: di Pr(T < t)	iff < 0 ) = <b>0.0133</b>	Pr(	Ha: diff != T  >  t ) = (	0 Ha: diff > 0 0.0265 Pr(T > t) = 0.9867	

## Independent sample t-test

Separate sample t test:

$$= \frac{y - x}{\left(\frac{(n_y - 1)s_x^2 + (n_x - 1)s_y^2}{n_x + n_y - 2}\right)^{1/2} \left(\frac{1}{n_x} + \frac{1}{n_y}\right)^{1/2}}$$
$$\frac{df = n_x + n_y - 2}{df = n_x + n_y - 2}$$

### Satterthwaite (1946) and Welch (1997) df corrections for unequal variances Stata Release 10 Reference Guide Q-Z (2007). StataCorp: College Station, Tx: 539.

Stata Release 10 Reference Guide Q-2 (2007). Statacorp. College Station, 1X. 555.

Satterthwaite's df (for unequal variances) = v Welch's (1997) df = w







## Welch's correction for unequal variances

. ttest lwt, by(smoke) welch

#### Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]			
0	115	130.9043	2.6501	28.41916	125.6545	136.1542			
1	74	128.1351	3.927628	33.78673	120.3074	135.9629			
combined	189	129.8201	2.224015	30. 57 51 5	125.4329	134.2073			
diff		2.769213	4.738068		-6. 599347	12.13777			
diff =	$diff = mean(0) - mean(1) \qquad t = 0.5845$								
Ho: diff =	Ho: diff = 0 Welch's degrees of freedom = <b>138.065</b>								
Ha: d	iff < 0	Pr(	Ha: diff !=	0	Ha: d	iff > 0			
Pr(T < t)	) = <b>0.7201</b>		T  >  t ) =	0. 5599	Pr(T > t	) = <b>0.2799</b>			

## Paired t-test

. save bpwide file bpwide.dta saved

ttest bp_before=bp_after

Paired t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]	
bp_bef~e bp_after	120 120	156.45 151.3583	1.039746 1.294234	11.38985 14.17762	154.3912 148.7956	158.5088 153.921	
diff	120	5.091667	1.525736	16.7136	2.070557	8.112776	
<pre>mean(diff) = mean(bp_before - bp_after) Ho: mean(diff) = 0 t = 3.3372 degrees of freedom = 119</pre>							
Ha: mean( Pr(T < t)	(diff) < 0 ) = <b>0.9994</b>	Ha Pr(	: mean(diff) T  >  t ) =	!= 0 0.0011	Ha: mean Pr(T > t	(diff) > 0 (diff) = <b>0.0006</b>	

paired  $t = \frac{\overline{x}_{2i} - \overline{x}_{1i}}{sd}$ 

df = n - 1

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# ANOVAs for comparisons of more than two means

#### Anova

- Main effects
  - Fixed
  - Random
  - Mixed
- Interactions
  - Proper specification
  - Plots
  - Tests of
- Repeated measures models
- Anova postestimation
  - Contrasts
  - Post-hoc tests with multiple comparison adjustments
  - Assumptions
    - Linearity
    - iid observations
    - Residual diagnostics
      - Homogeneity tests
      - Normality tests
      - Outlier detection(developed by R. A. Fisher)

R. A. Fisher



Sir Ronald Aylmer Fisher (1890-1962)

MStotal = MS betweenGroups + MS WithinGroups(error)

 $\sum_{i=1}^{n} \frac{(y_i - \overline{\overline{y}})^2}{n-1} = \sum_{i=1}^{n} \frac{(\overline{y}_i - \overline{\overline{y}})^2}{k-1} + \sum_{i=1}^{n} \frac{(y_i - \overline{y}_i)^2}{n-k}$ 

Total variance = Model variance + error variance

The {Omnibus} F test (named after R.A. Fisher) Anova model variance F(mdf, edf) =error variance  $R^2$ k-1F(k, n-k) = $1 - R^2$ n-k

### Interaction terms

- Sum of squares df Variance
- SSx # x levels 1 SSx/(xlev-1)
- SSy # y levels 1 SSy /(ylev-1)
- SSx * SSy (x-1)(y-1) Ssxy/(ylev-1)(xlev-1)

- Proper specification
- X Y and x*y must all be in the model

# One-Way ANOVA with residual diagnostics

	. anova systo	lic drug, par	tial detail					
	Factor	Value	Value		Value	Value		
ł	drug	11	2 2		33	44		
1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 -			Number of obs Root MSE	= = 10	58 .7211	R-squared Adj R-squared	= 0.3355 = 0.2985	
		Source	Partial SS	df	MS	F	Prob > F	
1 1		Model	3133.23851	3	1044.412	84 9.09	0.0001	
		drug	3133.23851	3	1044.412	84 9.09	0.0001	
		Residual	6206.91667	54	114.9429	01		
		Total	9340.15517	57	163.8623	71		
	. predict res1	L, residual						
ALC: NOT THE REAL PROPERTY IN	. jb res1 Jarque-Bera normality test: <b>2.211</b> Chi( <b>2</b> ) <b>.331</b> Jarque-Bera test for Ho: normality:							
1	. swilk res1							
144	Variable	Shapiro Obs	o-wilk w test f W	or no V	rmal data z	Prob>z		
	res1	58 (	0.98023 1.	046	0.097	0.46149		
	. hettest res1	L						
ALC: NO	Breusch-Pagan Ho: C Varia	/ Cook-Weisk Constant vari ables: res1	oerg test for h iance	etero	skedastic	ity		
	chi2( Prob	( <b>1</b> ) = > chi2 =	6.57 0.0104					
1								

#### Heteroscedasticity problem

### **One-way ANOVA with post-hoc tests**

oneway systolic drug, sidak tabulate Summary of Increment in Systolic B.P. Std. Dev. Drug Used Mean Freq. 1 26.066667 11.677002 15 2 25.533333 11.61813 15 3 8.75 10.0193 12 4 13.5 9.3238047 16 58 Total 18.87931 12.800874 Analysis of Variance Source SS df MS F Prob > FBetween groups 3133.23851 3 1044.41284 9.09 0.0001 114.942901 Within groups 6206.91667 54 9340.15517 163.862371 Total 57 Bartlett's test for equal variances: chi2(3) = 1.0063 Prob>chi2 = 0.800 Comparison of Increment in Systolic B.P. by Drug Used (Sidak) Row Mean-Col Mean 1 2 3 2 -. 533333 1.000 3 -17.3167 -16.78330.001 0.001 4 -12.5667 -12.0333 4.75 0.011 0.017 0.824

## Nonparametric one-way alternative

### Kruskall-Wallis one way nonparametric ANOVA

kwallis systolic, by(drug)

Kruskal-Wallis equality-of-populations rank test

drug	Obs	Rank Sum
1	15	581.00
2	15	587.50
3	12	189.00
4	16	353.50

chi-squared = **20.433** with **3** d.f. probability = **0.0001** 

chi-squared with ties = **20.457** with **3** d.f. probability = **0.0001** 

Distribution free one-way nonparametric ANOVA by rank sum

## Kruskall -Wallis nonparametric multiple comparisons

tal	b d	ru	g1
-----	-----	----	----

drug1	Freq.	Percent	Cum.
0 1	43 15	74.14 25.86	74.14 100.00
Total	58	100.00	

kwallis systolic, by(drug1)

Kruskal-Wallis equality-of-populations rank test

drug1	Obs	Rank Sum
0	43	1130.00
1	15	581.00

chi-squared = 6.049 with 1 d.f. probability = 0.0139 chi-squared with ties = 6.056 with 1 d.f. probability = 0.0139

## Main effects ANOVA

#### anova systolic drug disease

	Number of obs Root MSE	= = 10	58 R-so .5503 Adj	quared = R-squared =	= 0.3803 = 0.3207
Source	Partial SS	df	MS	F	Prob > F
Model	3552.07225	5	710.414449	6.38	0.0001
drug disease	3063.43286 418.833741	3 2	1021.14429 209.41687	9.17 1.88	0.0001 0.1626
Residual	5788.08293	52	111.309287		
Total	9340.15517	57	163.862371		

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## **Factorial Anova**

	. anova systolic	drug dise	ase drug*disea	se			
H I			Number of obs Root MSE	= = 10	58 R-s 5096 Adj	quared = R-squared =	0.4560 0.3259
-		Source	Partial SS	df	MS	F P	rob > F
Ē		Model	4259.33851	11	387.212591	3.51	0.0013
III.	drug	drug disease *disease	2997.47186 415.873046 707.266259	3 2 6	999.157287 207.936523 117.87771	9.05 1.88 1.07	0.0001 0.1637 0.3958
10		Residual	5080.81667	46	110.452536		
		Total	9340.15517	57	163.862371		
	. test drug, sym _cons 0 drug 1 r 2 r 3 r 4 -( disease 1 0 2 0 3 0 drug*disease 1 1 1 1 2 1 1 3 1 2 2 1 1 3 1 2 2 1 3 3 1 3 3 1 3 3 1 4 1 -1 4 2 -1 4 3 -1	bolic 1 2 3 (r1+r2+r3) /3 r1 /3 r1 /3 r2 /3 r2 /3 r2 /3 r2 /3 r3 /3 r3 /3 r3 /3 (r1+r2+ /3 (r1+r2+ /3 (r1+r2+	-r 3) -r 3) -r 3)				

## Anova Contrasts

. test drug, symbolic _cons 0 drug 1 r1 2 r2 3 r3 4 -(r1+r2+r3) disease 1 0 2 0 3 0 drug*disease 1 1/3 r1 1 2 1/3 r1 1 3 1/3 r1 2 1 1/3 r2 2 2 1/3 r2 2 3 1/3 r2 2 3 1/3 r3 3 2 1/3 r3 3 3 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 5 test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 CopyFigN@2009=RobertAddm?affee.PH	
$\begin{array}{c} cons & 0 \\ drug \\ 1 & r1 \\ 2 & r2 \\ 3 & r3 \\ 4 & -(r1+r2+r3) \\ disease \\ 1 & 0 \\ 2 & 0 \\ 3 & 0 \\ drug*disease \\ 1 & 1 & 1/3 r1 \\ 1 & 2 & 1/3 r1 \\ 2 & 1 & 1/3 r2 \\ 2 & 2 & 1/3 r2 \\ 2 & 2 & 1/3 r2 \\ 2 & 3 & 1/3 r3 \\ 3 & 2 & 1/3 r3 \\ 3 & 3 & 1/3 r3 \\ 4 & 1 & -1/3 (r1+r2+r3) \\ 4 & 2 & -1/3 (r1+r2+r3) \\ 4 & 3 & -1/3 (r1+r2+r3) \\ 4 & 3 & -1/3 (r1+r2+r3) \\ \end{array}$ . test _coef[drug[1]] = _coef[drug[2]] (1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 \\ . test _coef[drug[1]] = _coef[drug[3]] \\ (1) drug[1] - drug[3] = 0 \\ F( 1, 46) = 2.85 Copyrigh@2059=Robert.0982 affee. Pt \\ \end{array}	. test drug. symbolic
drug 1 r1 2 r2 3 r3 4 -(r1+r2+r3) disease 1 0 2 0 3 0 drug*disease 1 1 1/3 r1 1 2 1/3 r1 1 3 1/3 r1 2 1 1/3 r2 2 2 1/3 r2 2 3 1/3 r2 3 1 1/3 r3 3 2 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 5 test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 CopyFigN@2009=RobertAdam?affee.PH	cons 0
arug 1 r1 2 r2 3 r3 4 -(r1+r2+r3) disease 1 0 2 0 3 0 drug*disease 1 1 1/3 r1 1 2 1/3 r1 2 1/3 r2 2 2 1/3 r2 2 3 1/3 r2 3 1 1/3 r3 3 2 1/3 r3 3 2 1/3 r3 3 3 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 5 test _coef[drug[1]] = _coef[drug[2]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 CopyFigN@2009=Robert.0982affee.PH	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	arug
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	1 r1
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2
$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	
4 -(r1+r2+r3) disease $1 0$ $2 0$ $3 0$ drug*disease $1 1 1/3 r1$ $1 2 1/3 r1$ $1 3 1/3 r1$ $2 1 1/3 r2$ $2 2 1/3 r2$ $2 3 1/3 r2$ $3 1 1/3 r3$ $3 2 1/3 r3$ $3 2 1/3 r3$ $4 1 -1/3 (r1+r2+r3)$ $4 2 -1/3 (r1+r2+r3)$ $4 3 -1/3 (r1+r2+r3)$ $4 3 -1/3 (r1+r2+r3)$ $4 3 -1/3 (r1+r2+r3)$ $(1) drug[1] - drug[2] = 0$ $F( 1, 46) = 0.12$ $Prob > F = 0.7272$ $f( 1, 46) = 0.7272$ $f( 1, 46) = -coef[drug[3]]$ $f( 1) drug[1] - drug[3] = 0$ $F( 1, 46) = 2.85$ $Copyright 2009=Robert (Add Paffee, Phere)$	3 <b>F3</b>
disease 1 0 2 0 3 0 drug*disease 1 1 1/3 r1 1 2 1/3 r1 1 3 1/3 r1 2 1 1/3 r2 2 2 1/3 r2 2 3 1/3 r3 3 2 1/3 r3 3 2 1/3 r3 3 3 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] (1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copy[ight@2009=RobertAlaff affee.Pf	4 –(r1+r2+r3)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	disease
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 0
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 0
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2 0
drug*disease 1 1 1/3 r1 1 2 1/3 r1 1 3 1/3 r1 2 1 1/3 r2 2 2 1/3 r2 2 3 1/3 r3 3 2 1/3 r3 3 2 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] (1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright @2009 Robert Alan Yaffee. Ph	30
1 1 1/3 r1 1 2 1/3 r1 1 3 1/3 r1 2 1 1/3 r2 2 2 1/3 r2 2 3 1/3 r2 3 1 1/3 r3 3 2 1/3 r3 3 2 1/3 r3 3 3 1/3 r3 4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] (1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright @2009 Robert Alan Yaffee. Ph	drug*disease
$     \begin{array}{r}         1 & 1 & 1/3 \ r1 \\         1 & 2 & 1/3 \ r1 \\         1 & 3 & 1/3 \ r1 \\         2 & 1 & 1/3 \ r2 \\         2 & 2 & 1/3 \ r2 \\         2 & 3 & 1/3 \ r2 \\         3 & 1 & 1/3 \ r3 \\         3 & 2 & 1/3 \ r3 \\         3 & 2 & 1/3 \ r3 \\         4 & 1 & -1/3 \ (r1+r2+r3) \\         4 & 3 & -1/3 \ (r1+r2+r3) \\         4 & 3 & -1/3 \ (r1+r2+r3) \\         t est _coef[drug[1]] = _coef[drug[2]] \\         (1) \ drug[1] - drug[2] = 0 \\         F( \ 1, \ 46) = \ 0.12 \\         Prob > F = \ 0.7272 \\         test _coef[drug[1]] = _coef[drug[3]] \\         (1) \ drug[1] - drug[3] = 0 \\         F( \ 1, \ 46) = \ 2.85 \\         Copyright @209 = Robert Alan Yaffee. Press         $	urug ursease
1 2 $1/3 r1$ 1 3 $1/3 r1$ 2 1 $1/3 r2$ 2 2 $1/3 r2$ 2 3 $1/3 r2$ 3 1 $1/3 r3$ 3 2 $1/3 r3$ 3 2 $1/3 r3$ 4 1 $-1/3 (r1+r2+r3)$ 4 2 $-1/3 (r1+r2+r3)$ 4 3 $-1/3 (r1+r2+r3)$ 5 test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 5 test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph	1 1 <b>1/3 r1</b>
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	1 2 <b>1/3 r1</b>
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 3 1/3 r1
$2 1 1/3 r^{2}$ $2 2 1/3 r^{2}$ $2 3 1/3 r^{3}$ $3 1 1/3 r^{3}$ $3 2 1/3 r^{3}$ $4 1 -1/3 (r^{1}+r^{2}+r^{3})$ $4 2 -1/3 (r^{1}+r^{2}+r^{3})$ $4 3 -1/3 (r^{1}+r^{2}+r^{3})$ $4 3 -1/3 (r^{1}+r^{2}+r^{3})$ $(1) drug[1] - drug[2] = 0$ $F( 1, 46) = 0.12$ $Prob > F = 0.7272$ $f( 1, 46) = 0.7272$ $f( 1, 46) = 0.12$ $Prob > F = 0.7272$ $f( 1, 46) = 0.7272$	
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2 3 $1/3$ r2 3 1 $1/3$ r3 3 2 $1/3$ r3 3 2 $1/3$ r3 4 1 $-1/3$ (r1+r2+r3) 4 2 $-1/3$ (r1+r2+r3) 4 3 $-1/3$ (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyrigh @ 2009 Robert Alan Yaffee. Ph	2 2 <b>1/3 r2</b>
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2 3 <b>1/3 r2</b>
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$2 1 1/2 r^2$
$3 2 1/3 r^{3}$ $3 3 1/3 r^{3}$ $4 1 -1/3 (r^{1}+r^{2}+r^{3})$ $4 2 -1/3 (r^{1}+r^{2}+r^{3})$ $4 3 -1/3 (r^{1}+r^{2}+r^{3})$ $4 3 -1/3 (r^{1}+r^{2}+r^{3})$ $(1) drug[1] - drug[2] = 0$ $F( 1, 46) = 0.12$ $Prob > F = 0.7272$ $f( 1, 46) = 0.7272$ $f( 1, 46) = -coef[drug[3]]$ $f( 1) drug[1] - drug[3] = 0$ $F( 1, 46) = 2.85$ $Copyrigh @ 209 = Robert Alam Yaffee. Phenetic Product of the second state of the s$	5 1 1/515
3 3 $1/3 r^3$ 4 1 $-1/3 (r^1+r^2+r^3)$ 4 2 $-1/3 (r^1+r^2+r^3)$ 4 3 $-1/3 (r^1+r^2+r^3)$ . test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph	3 2 <b>1/3 r3</b>
4 1 -1/3 (r1+r2+r3) 4 2 -1/3 (r1+r2+r3) 4 3 -1/3 (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph	3 3 <b>1/3 r3</b>
$\begin{array}{rrrrr} 4 & 2 & -1/3 & (r1+r2+r3) \\ 4 & 3 & -1/3 & (r1+r2+r3) \\ 4 & 3 & -1/3 & (r1+r2+r3) \\ \end{array}$ $\begin{array}{rrrrr} \text{test _coef[drug[1]] = _coef[drug[2]]} \\ (1) & drug[1] - drug[2] = 0 \\ F(1, 46) = 0.12 \\ Prob > F = 0.7272 \\ \end{array}$ $\begin{array}{rrrr} \text{test _coef[drug[1]] = _coef[drug[3]]} \\ (1) & drug[1] - drug[3] = 0 \\ F(1, 46) = 2.85 \\ Copyright @ 2009 = Robert Alan Yaffee. Phase Problem (Alan Yaffee. Phase P$	$4 \ 1 \ -1/3 \ (r1+r2+r3)$
$4 \ 2 \ -1/3 \ (r1+r2+r3) \\ 4 \ 3 \ -1/3 \ (r1+r2+r3) \\ . test _coef[drug[1]] = _coef[drug[2]] \\ (1) \ drug[1] - drug[2] = 0 \\ F( \ 1, \ 46) = \ 0.12 \\ Prob > F = \ 0.7272 \\ . test _coef[drug[1]] = _coef[drug[3]] \\ (1) \ drug[1] - drug[3] = 0 \\ F( \ 1, \ 46) = \ 2.85 \\ Copyright @2009 Robert Alan Yaffee. Pherical Science (Prob$	4 - 1/2 (1112113)
4 3 -1/3 (r1+r2+r3) . test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph	4 2 -1/3 (11+12+13)
<pre>. test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph </pre>	4 3 <b>-1/3 (r1+r2+r3)</b>
<pre>. test _coef[drug[1]] = _coef[drug[2]] ( 1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph </pre>	
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<pre>(1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alam Paffee. Ph Copyright@2009=Robert Alam Paffee. Ph </pre>	$- cost _cost [u ug[1]] - _cost [u ug[2]]$
<pre>(1) drug[1] - drug[2] = 0 F( 1, 46) = 0.12 Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] (1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Pr Copyright@2009=Robert Pr Copyright@2009</pre>	
F( 1, 46) = 0.12 Prob > F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph	(1) drug[1] – drug[2] = 0
<pre>F( 1, 46) = 0.12 Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 F( 1, 46) = 2.85 Copyright@2009=Robert Alam Yaffee. Phere Phere</pre>	· · · · · · · · · · · · · · · · · · ·
<pre>     F(1, 40) = 0.12     Prob &gt; F = 0.7272  . test _coef[drug[1]] = _coef[drug[3]]   (1) drug[1] - drug[3] = 0     F( 1, 46) = 2.85         Copyright@2009=Robert Alan Yaffee. Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Copyright@2009=Robert Alan Yaffee.         Ph         Ph         Ph</pre>	F(1 - 46) = 0.12
<pre>Prob &gt; F = 0.7272 . test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 F( 1, 46) = 2.85 Copyright@2009=Robert Alam Yaffee. Prob Copyright@2009=Robert Alam Yaffee. Prob Cop</pre>	F(1, 40) = 0.12
<pre>. test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alam Yaffee. Phere</pre>	Prob > F = 0.7272
<pre>. test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert.Alan Yaffee.Ph Copyright@2009=Robert.Alan Yaffee.Ph</pre>	
<pre>. test _coef[drug[1]] = _coef[drug[3]] ( 1) drug[1] - drug[3] = 0 F( 1, 46) = 2.85 Copyright@2009=Robert Alan Yaffee. Ph Copyright@2009=Robert Ph Copyright@2009=Robert Ph Copyrigh</pre>	
(1) $drug[1] - drug[3] = 0$ F(1, 46) = 2.85 Copyright @2009=Robert Alan Yaffee. Ph	tost $coof[dnua[1]] = coof[dnua[2]]$
(1) drug[1] - drug[3] = 0 F(1, 46) = 2.85 Copyright @ $2009^{=}$ Robert Alan Yaffee. Ph	resc _coer[arud[1]] = _coer[arud[3]]
(1) drug[1] - drug[3] = 0 F(1, 46) = 2.85 Copyright @ 2009 = Robert Alan Yaffee. Ph	
F(1, 46) = 2.85 F(1) = 0.0982 Copyright @ 2009 = Robert Alan Yaffee. Ph	(1) drug[1] - drug[3] = 0
F( 1, 46) = 2.85 Copyright@2009 ⁼ Robert Alan Yaffee, Ph	
Copyright @2009 Robert Alan Vaffee. Ph	F(1, 46) = 2.85
Copyright @2009 Robert Alan Yaffee. Ph	Prob > E = 0.0092
	Copyright @2009 Robert Alan Yaffee, P

Ph.D.

## Arguments to pass on

#### ereturn list

scalars:

e(N) =	58
e(df_m) =	5
e(df_r) =	52
e(F) =	6.382346596518431
e(r2) =	. 3803012028033359
e(rmse) =	10.55032165566441
e(mss) =	3552.072246438768
e(rss) =	5788.082925975032
e(r2_a) =	. 3207147799959643
e(11) =	-215.7887236513469
$e(11_0) =$	-229.6658538202016
$e(ss_1) =$	3063.432863498659
e(df_1) =	3
$e(F_1) =$	9.173936110869594
$e(ss_2) =$	418.8337406916411
e(df_2) =	2
e(F_2) =	1.881396206179656

macros:

e(cmdline)	:	"anova systolic drug disease"
e(depvar)	:	"systolic"
e(cmd)	1	"anova"
e(properties)	1	"b_nonames V_nonames"
e(varnames)	1	"drug disease"
e(term_2)	1	"disease"
e(term_1)	1	"drug"
e(sstype)	1	"partial"
e(predict)	1	"regres_p"
e(model)	1	"ols"
e(estat_cmd)	1	"anova_estat"
icos:		

matrices:

e(b) : 1 x 8 e(V) : 8 x 8

## **ANOVA** Postestimation



## lvr2plot



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## Full-factorial model and model comparison

anova systolic drug disease drug*disease

		Number of obs Root MSE	= = 10	58 . 5096	R-squared Adj R-squared	= 0.4560 = 0.3259
	Source	Partial SS	df	MS	F	Prob > F
	Model	4259.33851	11	387.21259	1 3.51	0.0013
	drug disease drug*disease	2997.47186 415.873046 707.266259	3 2 6	999.15728 207.93652 117.8777	7         9.05           3         1.88           1         1.07	0.0001 0.1637 0.3958
	Residual	5080.81667	46	110.45253	6	
	Total	9340.15517	57	163.86237	1	
est store	factorial					
est save f ile factori	actorial al.ster saved					

```
. est stats _all
```

Model	Obs	11(null)	11(model)	df	AIC	BIC
maineffects	58	-229.6659	-215.8616	5	441.7231	452.0253
factorial	58	-229.6659	-212.0092	12	448.0184	472.7437

Note: N=Obs used in calculating BIC; see [R] BIC note

# Final model with residual normality diagnosis

anova systolic drug disease, class(drug)

	Number of obs Root MSE	= = 10	58 R-so .4634 Adj	quared R-squared	= 0.3787 = 0.3319
Source	Partial SS	df	MS	F	Prob > F
Model	3537.51561	4	884.378902	8.08	0.0000
drug disease	3063.89117 404.277102	3 1	1021.29706 404.277102	9.33 3.69	0.0000 0.0600
Residual	5802.63956	53	109.483765		
Total	9340.15517	57	163.862371		

predict res1, residual

swilk res1

Variable	Shapi Obs	ro-Wilk W W	test for normal V	l data z	Prob>z
res1	58	0.96278	1.969	1.457	0.07251

## Graphical review of residuals



## Nonparametric Friedman 2-way ANOVA written in Stata by Richard Goldstein

- Type: findit friedman
- Install snp-1

use gibbons2, clear

list

	<b>s1</b>	<b>s</b> 2	<b>s</b> 3	<b>s4</b>	<b>s</b> 5	<mark>56</mark>	<b>s</b> 7	<b>s8</b>
1.	90	60	45	48	58	72	25	85
2.	62	81	92	76	70	75	95	72
3.	60	91	85	81	90	76	93	80

		_	
~	noco		0.00
	DUSE.	_	ear
	,	_	

list

	<b>v1</b>	<b>v</b> 2	v3
	90	62	60
	60	81	91
	45	92	85
	48	76	81
	58	70	90
5.	72	75	76
7.	25	95	93
3.	85	72	80

. friedman v1-v3 Friedman = 2.8889 Kendall = 0.1376 p-value = 0.8951

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## **Repeated measures ANOVAs**

. anova mise	aby chile in	groupr, rep	careu	ermey			
		Number of ob Root MSE	s = = .4	16 09681	R-squa Adj R-s	red = squared =	0.9388 0.8979
	Source	Partial SS	df	MS		F P	rob > F
	Model	23.1592161	6	3.85986	934	23.00	0.0001
	dog time	16.9024081 6.25680792	3 3	5.63413 2.08560	604 264	33.57 12.43	0.0000 0.0015
	Residual	1.51054662	9	.167838	513		
	Total	24.6697627	15	1.64465	084		
Between-subjec Lowest b.	ts error ter Leve s.e. variab	rm: dog ls: <b>4</b> le: dog	(3 df	)			
Repeated varia	ble: time		Huy Gre Box	nh-Feldt enhouse- 's conse	epsilon Geisser rvative	= epsilon = epsilon =	0.5376 0.4061 0.3333
	Source	df	F R	egular	— Prob H-F	> F G-G	Вох
	time Residual	3 12 9	.43	0.0015	0.0138	0.0267	0.0388

apova lhist dog time if aroun=1 repeated(time)

## **Repeated measures ANOVAs**

anova lhist group / dog|group time time*group if dog !=6, repeated(time)

	Number of obs Root MSE	=	60 F 27427 /	R-squared Adj R-squared	= 0.9709 = 0.9479
Source	Partial SS	df	MS	F	Prob > F
Model	82.6836382	26	3.1801399	3 42.28	0.0000
group dog group	27.0286268 24.3468341	3 11	9.00954220 2.2133485	6 <b>4.</b> 07	0.0359
time time*group	12.0589871 17.5232918	3 9	4.01966233 1.94703243	5 53.44 3 25.88	0.0000
Residual	2.48238892	33	.075223907	7	
Total	85.1660271	59	1.4434919	9	

Between-subjects error term: dog|group Levels: 15 (11 df) Lowest b.s.e. variable: dog Covariance pooled over: group (for repeated variable) Repeated variable: time Huynh-Feldt epsilon = 0.8475 Greenhouse-Geisser epsilon = 0.5694 Box's conservative epsilon = 0.3333

Source	df	F	Regular	—— Prob H-F	> F G-G Box	
time time*group Residual	3 9 33	53.44 25.88	0.0000 0.0000	0.0000 0.0000	0.0000 0.0000	0.0000

Fixed, random, and mixed effects models

- Fixed effects are clearly specified with all levels being sampled-e.g., gender.
- Random effects are those which are supposedly randomly sampled with only some of the levels included in the study: e.g., subjects.
- Mixed effects models have both fixed and random effects in the model.

The error variance for such effects differ and therefore must be clearly identified.

 F tests have to be properly constructed with these different effects.

## **Expected mean squares (Variances)**

#### **Expected Mean Squares for Different Designs**

Source: Michaels, Brown, & Winer, 1993, Statistical Principles of Experimental Design, 304

	Case 1: Fixed	Case 2: Mixed	Case 3: Random		
	a fixed, b fixed	a fixed b random	a random b random		
MS _a	$\sigma_e^2 + nq\sigma_a^2$	$\sigma_e^2 + n\sigma_{ab}^2 + nq\sigma_a^2$	$\sigma_e^2 + n\sigma_{ab}^2 + nq\sigma_a^2$		
Ms _b	$\sigma_e^2 + nq\sigma_b^2$	$\sigma_e^2$ + $np\sigma_b^2$	$\sigma_e^2 + n\sigma_{ab}^2 + np\sigma_b^2$		
MS _{ab}	$\sigma_e^2 + n\sigma_{ab}^2$	$\sigma_e^2 + n\sigma_{ab}^2$	$\sigma_e^2 + n\sigma_{ab}^2$		
MS erro	$\sigma_e^2$	σ _e ²	σ _e ²		

F test for fixed effect =  $MS_a/MS_{error}$ F test for random effect =  $MS_b/MS_{error}$ F-test for mixed effect : fixed =  $MS_a/Ms_{ab}$  Random

Random=MS_b/MS_{error}

## Repeated measures with wsanova

. wsanova lhist time if group==1, id(dog) epsilon

	Number of obs Root MSE	= = .4(	16 R 09681 A	-squared dj R-squared	= 0.9388 = 0.8979
Source	Partial SS	df	MS	F	Prob > F
dog time Residual	16.9024081 6.25680792 1.51054662	3 3 9	5.63413604 2.08560264 .167838513	12.43	0.0015
Total	24.6697627	15	1.64465084	4	

Note: Within subjects F-test(s) above assume sphericity of residuals; p-values corrected for lack of sphericity appear below.

Greenhouse-Geisser (G-G) epsilon: **0.4061** Huynh-Feldt (H-F) epsilon: **0.5376** 

+			PT UU > F	PT 00 2 F	PI 00 2 F
Source	df	F	Prob > F	G-G Prob > F	H-F Prob > F

## **Residual diagnostics**

🔟 Stata Graph - Graph		
<u> </u>	<u>H</u> elp	
💀 📾 🖨 📭 🛍 🔜 🖈	6 2	
📶 Graph		4 Þ ×
Margh N, 1 Margh N, 2	Marph N, 3	Marph N, 4
÷	-	
Margh Y, 5 Margh Y, 6	Margh Y, 7	Margh Y, S
*	T	Tests N. 17
1 Tmelh Y, 12 Tmelh Y, 14 € 4	Tmeth Y, 15	Tmelh Y, 16
ó só só Minutes after inje	ction s o	÷
Residuals     Fitted values	95% CI	
Graphs by Experimental group and Dog no.		
twoway (scatter rmres tin ote: regress could not f	ne) (qfitci it model)	rmres ti

# Within-subject residual serial correlation confirmed

	. gen rmresx2 = rmresx^2 (4 missing values generated)							
	. regress rmre	regress rmresx2 group time dog						
	Source	SS	df	MS		Number of obs = $60$		
	Model Residual	.086291045 .379461186	3 .028763682 56 .006776093			Prob > F = 0.0090 R-squared = 0.1853		
	Total	.465752232	59	.007894106		Root MSE = $.08232$		
	rmresx2	Coef.	Std. E	rr. t	P> t	[95% Conf. Interval]		
	group time dog _cons	0316901 0133025 .0018365 .1356686	.03808 .00553 .00926 .03154	36         -0.83           41         -2.40           61         0.20           51         4.30	0.409 0.020 0.844 0.000	1079807 .0446006 02438860022163 0167258 .0203989 .072476 .1988611		
. regress rmres2 group dog grxdog								
	Source	SS	df	MS		Number of obs = $60$		
	Model Residual	.048898111 .416854121	3 56	.01629937 .007443824		Prob > F = 0.0994 R-squared = 0.1050 Adi R-squared = 0.0570		
	Total	. 4657 52232	59	.007894106		Root MSE = .08628		
	rmres2	Coef.	Std. E	rr. t	P> t	[95% Conf. Interval]		
	group dog grxdog _cons	0430226 0012478 .0012866 .1261824	.04622 .01160 .00264 .05188	68 -0.93 13 -0.11 71 0.49 55 2.43	0.356 0.915 0.629 0.018	1356259 .0495807 0244879 .0219924 0040161 .0065893 .0222432 .2301216		
# Residual diagnostics of heteroscedasticity

لللا Sta	ta Graph - Graph	ve – D 🛛	
<u>F</u> ile	<u>E</u> dit <u>O</u> bject <u>G</u> raph <u>T</u> oo	is <u>H</u> elp	
8	i 🖨 🕒 🛍 📃	* @ @   •    •	
hii Gr	raph	$\triangleleft \triangleright \times$	group)
	Residual variance by time	Residual variance by time	
	0	1	
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"			
S - t			
Ê	Residual variance by time	Residual variance by time	
1 ⁻ .	3	5	
<u>۹</u> .			
N			
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Graph	hs by Minutes after Injection		
- 91 OF			
. grap	oh box rmresx2, by(t	ime) title(Residual va	uriance by time)

#### George E. P. Box ("All models are wrong, but some happen to be useful."



### **Albert Einstein**

Institute of Advanced Studies Princeton, NJ

- Formulated the principle of parsimony: Keep it as simple as possible, but not simpler.
- So far as the theories of mathematics are about reality, they are not certain; so far as they are certain, they are not about reality.
- Do not worry about your difficulties in mathematics, I assure you that mine are greater.



Albert Einstein

Albert Einstein, 1921

# OLS regression analysis Adrien-Marie Legendre and C. F. Gauss



Adrien-Marie Legendre Mathematician (1752-1833)

#### **Regression models**

- Basic theory
- Graph the data first (graph matrix of dependent with candidate independent variables). Search for possible good relationships. (p. 105)
- Ask if transformations to linearity are needed? Power transformations? Regression splines for piecewise models?

#### Assumptions of Ordinary Least Squares (OLS) (classical) regression analysis

- Linear functional form
- Normality of residuals
- Homogeneity of variance
- Observations are iid. Errors are not correlated with the predictor variables.
- No outliers distorting the mean
- No multicollinearity
- Predictors are fixed or deterministic
  - If they are stochastic due to measurement error that could bias the model.

#### **Regression analysis**

developed by C.F. Gauss and Adrian Marie LeGendre

- Simple OLS theory if the dependent var is continuous
  - If assumptions are fulfilled
  - Polynomial regression
  - All possible subsets regression
- Problems with stepwise regression
- Regression postestimation
  - For normality
  - For heterogeneity of residuals
  - For multicollinearity
  - For functional form

### **Basic Regression model theory**



total = model + error $(y_i - \overline{y}) = (\hat{y}_i - \overline{y}) + (y_i - \hat{y}_i)$ we square these  $(y_i - \overline{y})^2 = (\hat{y}_i - \overline{y})^2 + (y_i - \hat{y}_i)^2$ we add all of them up to obtain total SS = model SS + error SS  $\sum_{i=1}^{n} (y_{i} - \overline{y})^{2} = \sum_{i=1}^{n} (\hat{y}_{i} - \overline{y})^{2} + \sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}$ *i*=1 *i*=1 i=1

Dividing the SS  $\sum_{i=1}^{n} (y_{i} - \overline{y})^{2} = \sum_{i=1}^{n} (\hat{y}_{i} - \overline{y})^{2} + \sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}$ by their respective df dft = n - 1 dfm = k dfe = n - k - 1gives MStotal = MS regression + MS error  $\sum_{i=1}^{n} \frac{(y_i - \bar{y})^2}{n-1} = \sum_{i=1}^{n} \frac{(\hat{y}_i - \bar{y})^2}{k} + \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n-k-1}$ *Total variance = Model variance + error variance* 

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# **Omnibus F test** regression model variance F(mdf, edf) =error variance $R^2$ k F(k, n - k - 1) = $1 - R^2$ n-k-1

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# We can solve for b

$$e_{i} = \hat{y}_{i} - y_{i}$$

$$e_{i}^{2} = (\hat{y}_{i} - y_{i})^{2}$$

$$\sum_{i=1}^{n} e_{i}^{2} = \sum_{i=1}^{n} (\hat{y}_{i} - y_{i})^{2} = \sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}$$

$$\sum_{i=1}^{n} e_{i}^{2} = \sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2} = \sum_{i=1}^{n} (y_{i} - a - bx_{i})^{2}$$

$$\frac{\partial \sum_{i=1}^{n} e_{i}^{2}}{\partial b} = \frac{\partial \sum_{i=1}^{n} (y_{i} - a - bx_{i})^{2}}{\partial b}$$

$$\theta = 2\sum xy - 2b\sum x^{2}$$

$$b = \frac{\sum_{i=1}^{n} xy}{\sum_{i=1}^{n} x^{2}}$$

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#### We can also solve for a

 $y_{i} = a + bx_{i}$ for each person sum for the whole sample:  $\sum_{i=1}^{n} y_{i} = n^{*}a + b\sum_{i}^{n} x_{i}$  $a = \overline{y} - b\overline{x}$ 

# Diagnosing functional form with a matrix graph



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### **Functional form**

- Are any of the foregoing plots indicative of possible nonlinear relationships?
- Which ones?
- Mpg and weight?
- Mpg and forxwt?

Frank E. Harrell Jr. (2001) <u>Regression Modeling Strategies</u>, Springer: New York. advocated using lowess and/or splines to model the nonlinearity found in most n relationships. Chapter 2.

#### A lowess plot



# **Polynomial regression**

. gen wt2 = weight^2

. gen forxwt2 = foreign*wt2

regress	mpg	weight	gear	foreign	forxwt	wt2	forxwt2

Source	SS	df	MS		Number of obs	= 74 - 26.93
Model Residual	1727.28735 716.172106	62 671	87.881226 0.6891359		Prob > F R-squared	= 0.0000 = 0.7069 = 0.6807
Total	2443.45946	73 3	3.4720474		Root MSE	= 3.2694
mpg	Coef.	Std. Er	r. t	P> t	[95% Conf.	Interval]
weight gear_ratio foreign forxwt wt2 forxwt2 _cons	0131966 1.799501 -2.761914 .002836 1.20e-06 -1.12e-06 44.73605	.004752 1.49526 23.550 .018537 7.32e-0 3.59e-0 9.08817	5       -2.78         1       1.20         4       -0.12         7       0.15         7       1.64         6       -0.31         4       4.92	0.007 0.233 0.907 0.879 0.105 0.756 0.000	0226827 -1.185053 -49.7687 0341654 -2.57e-07 -8.27e-06 26.59598	0037106 4.784054 44.24487 .0398374 2.66e-06 6.04e-06 62.87612

#### xi: Interaction analysis

- Macro for converting categorical data to dummy variables for analysis.
- The macro will also construct all of the main effects and first-order interaction terms for such an analysis.

# xi: and i. prefixes for dummy coding categorical variables with main effects

. list	-			_ /	/	. li	st						
	У	<b>x1</b>	<b>x</b> 2				v	x1	x2	Ix1 2	IX2 2	D	K2 3
1. 2. 3.	32 2 3	1 2 1	1 2 3			1. 2. 3.	3 2 3	1 2 1	1 2 3	0 1 0	0 1 0		0 0 1
5.	/ 2	1	2	/		4.	4	2	1	1	01		0
6. 7. 8.	8 10 32	2 1 1	3 1 2			6. 7. 8.	8 10 32	2 1 1	3 1 2	1 0 0	001		1 0 0
9. 10.	12 41	2	3			9. 10.	12 41	2	3	1	0		0
↓ . xi:r i.x1 i.x2	sourc	sy el	i.x1 · _I: _I:	i.x2 x1_1-2 x2_1-3 SS	df	()	(natura (natura MS	ally ally	code code	d; _Ix1_ d; _Ix2_ Number	1 omitt 1 omitt of obs	ed) ed) =	10
Re	Mode sidua	:1 .1	200. 1485	766667	3 6	66.92 247.9	222222			F( 3, Prob > R-squa	6) F red	= = ( = (	0.27 0.8448 0.1191
	Tota	1	:	1686.1	9	187.3	344444			Root M	SE	= 1	15.734
		У	(	Coef.	Std.	Err.	t	F	P> t	[95	% Conf.	Inte	erval]
	_IX1_ _IX2_	2	-1.8	-7.6	10.90 12.05	076 125	-0.70	5 0	0.512	-34. -31.	27321 35501	19. 27.	.07321

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# xi: and i.x1*i.x2 construct dummy variables for all main effects and interactions for the model

- ALL LOGICOS	y 1.71°1.72					
i.x1	_IX1_1-2		(natura	11y coded	; _IX1_1 omitt	ed)
1.X2	_Ix2_1-3		(natura	lly coded	; _Ix2_1 omitt	ed)
i.x1*i.x2	_IX1XX2_#	_#	(coded	as above)		
Source		df	мс		Number of obs	- 10
		- ui	110		E( 5. 4)	= 0.26
Model	410.1	5	82.02		Prob > F	= 0.9156
Residual	1276	4	319		R-squared	= 0.2432
					Adj R-squared	= -0.7027
Total	1686.1	9	187.344444		Root MSE	= 17.861
У	Coef.	Std.	Err. t	P> t	[95% Conf.	Interval]
IX1 2	-14	20.62	361 -0.68	0.534	-71,26032	43,26032
_IX2_2	-1	16.3	044 -0.06	0.954	-46.26826	44.26826
_IX2_3	-15	20.62	361 -0.73	0.507	-72.26032	42.26032
Tv1Vv2 2 2	-1	30.06	382 -0.03	0.975	-84.47055	82.47055
_171775_5_5						
_1x1xx2_2_3	21	30.06	382 0.70	0.523	-62.47055	104.4705

# OLS regression with some residual diagnostics

. webuse auto (1978 Automobile Data)

. regress mpg weight gear foreign

Source	SS	df	MS		Number of obs = F(3, 70) =	= 74 = 46.73
Model Residual	1629.67805 813.781411	3 543. 70 11.6	226016 254487		Prob > F = R-squared =	= 0.0000 = 0.6670 = 0.6527
Total	2443.45946	73 33.4	720474		Root MSE =	= 3.4096
mpg	Coef.	Std. Err.	t	P> t	[95% Conf. :	Interval]
weight gear_ratio foreign _cons	006139 1.457113 -2.221682 36.10135	.0007949 1.541286 1.234961 6.285984	-7.72 0.95 -1.80 5.74	0.000 0.348 0.076 0.000	0077245 -1.616884 -4.684735 23.56435	0045536 4.53111 .2413715 48.63835

predict resid, residual

. swilk resid

variable	74	0 84047	0.604	4 055	0.00000
Variable	Shap Obs	iro-wilk W w	test for norma	l data	Probsz

hettest resid

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: resid

> chi2(1) = 110.60 Prob > chi2 = 0.0000

# More residual diagnostics

. correlate we (obs=74)	eight gear f	foreign	
	weight g	gear_r~o	foreign
weight gear_ratio foreign	1.0000 -0.7593 -0.5928	1.0000 0.7067	1.0000
. vif			
Variable	VIF	1/	VIF
gear_ratio weight foreign	3.11 2.40 2.03	0.321 0.417 0.493	.991 207 8070

2.51

Mean VIF

#### **Other residual diagnostics**

. estat ovtest

Ramsey RESET test using powers of the fitted values of mpg Ho: model has no omitted variables F(3, 67) = 2.53 Prob > F = 0.0642

. estat imtest

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	р
Heteroskedasticity Skewness Kurtosis	12.02 8.49 1.70	8 3 1	0.1502 0.0368 0.1922
Total	22.22	12	0.0351

# Outlier diagnosis (residuals larger than 3 std errors)

. regress mpg	weight gear f	oreign			
Source	SS	df	MS		Number of obs = $74$
Model Residual	1629.67805 813.781411	3 543. 70 11.6	226016 254487		P(0, 7, 70) = 40.73 Prob > F = 0.0000 R-squared = 0.6670 Adj = 500000
Total	2443.45946	73 33.4	720474		Root MSE = $3.4096$
mpg	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
weight gear_ratio foreign _cons	006139 1.457113 -2.221682 36.10135	.0007949 1.541286 1.234961 6.285984	-7.72 0.95 -1.80 5.74	0.000 0.348 0.076 0.000	00772450045536 -1.616884 4.53111 -4.684735 .2413715 23.56435 48.63835

#### predict stdres, rstandard

extremes stdres

obs:	stdres
66.	-1.696421
18.	-1.4217749
70.	-1.2841784
62.	-1.2606142
67.	-1.1990003

17.         2.2235358           31.         2.4201789           65.         2.44714           61.         2.4637769           68.         4.2656077
-----------------------------------------------------------------------------------------------------------------------------------------------------

# Testing for influential outliers (Bollen, K. and Jackman, R.W., 1990)

* Bollen and Jackman say that 4/n is a high cooksd

di 4/74 05405405

list cooksd if cooksd > 4/74

	cooksd
31.	.10495095
59.	.0601601
60.	.07010017
61.	.09325021
65.	.07983294
66.	.06385328
68.	.26637057
70.	.05777313

list cooksd stdres if cooksd > 4/74

	cooksd	stdres
31.	.10495095	2.4201789
59.	.0601601	1.8078253
60.	.07010017	1.4436658
61.	.09325021	2.4637769
65.	.07983294	2.44714
66.	.06385328	-1.696421
68.	.26637057	4.2656077
70.	.05777313	-1.2841784

### Extremes cooksd

When Cook's distance > n/4 then it may be a problem

obs:	cooksd
11.	.00002704
53.	.00002988
36.	.00003338
28.	.00008491
73.	.00010401

60.         .07010017           65.         .07983294           61.         .09325021           31.         .10495095           68.         .26637057
-------------------------------------------------------------------------------------------------------------------------------------------------------

#### extremes stdres

obs:	stdres
66.	-1.696421
18.	-1.4217749
70.	-1.2841784
62.	-1.2606142
67.	-1.1990003

17.	2.2235358
31.	2.4201789
65.	2.44714
61.	2.4637769
68.	4.2656077

# How can you deal with the extreme values? Winsorizing

	. stem	n mpg
and the state of the state of the state	Stem-a	and-leaf plot for mpg (Mileage (mpg))
	1t 1f 1s 1. 2* 2t 2f	22 44444455 66667777 888888888899999999 00011111 22222333 444455555
Taking the	25 2. 3*	666 8889 001
extreme non-	3t 3f	455
missing ordered	3s 2	
values of x and	4*	1
sets equal to the	. wins	or mpg, gen(wmpg) p(.1)
next highest and	. sten	1 wmpg
lowest values.	Stem-a 1f 1s 1. 2* 2t 2f 2s	and-leaf plot for wmpg (mpg, Winsorized fraction .1) 4444444455 66667777 8888888888999999999 00011111 22222333 444455555 666
	2t 2f 2s 2.	2222233 444455555 666 88899999999

•

z.

#### **Automatic Interaction construction**

First check the variables for missing values

E			
F D D Free	q. f	Percent	Cum.
8 2 3 4 8 8 8	52 10 67 52	20.88 37.00 21.24 20.88	20.88 57.88 79.12 100.00
4,0	81	100.00	
, nolabel			
F 1 0 Frei	q. 1	Percent	Cum.
8 2 <b>1,5</b> 3 <b>8</b> 4 <b>8</b>	52 10 67 52	20.88 37.00 21.24 20.88	20.88 57.88 79.12 100.00
4,0	81	100.00	
c, nolabel m	issing		
F D D Free	q. f	Percent	Cum.
L 8 2 1,5 3 8 4 8 4 2	52 10 67 52 09	19.86 35.20 20.21 19.86 4.87	19.86 55.06 75.27 95.13 100.00
	Free Free Free Free Free Free Free Free	Freq. 6 Freq. 7 Freq. 6 Freq. 7 Freq. 7 Fre	Freq.       Percent         8       852       20.88         1,510       37.00         867       21.24         852       20.88         4       852       20.88         4       4,081       100.00         5, nolabel       5         6       Freq.       Percent         7       852       20.88         1, 510       37.00         867       21.24         852       20.88         1, 510       37.00         867       21.24         852       20.88         1, 510       37.00         867       21.24         852       20.88         1, 510       37.00         867       21.24         852       19.86         1, 510       35.20         867       20.21         852       19.86         209       4.87

#### **Construct dummy variables**

	quietly	tabulate	edcat,	generate(	(educd)
--	---------	----------	--------	-----------	---------

. describe educd1-educd4

variable name	storage type	displa format	y va la	llue bel va	riable label
educd1 educd2 educd3 educd4	byte byte byte byte	%8.0g %8.0g %8.0g %8.0g %8.0g		ed ed ed	cat= 1.0000 cat= 2.0000 cat= 3.0000 cat= 4.0000
. tab educd1					
edcat== 1.0000	Fred	4.	Percent	Cum.	
0 1	3,22 85	29 52	79.12 20.88	79.12 100.00	
Total	4,08	81	100.00		
. tab educd2					
edcat== 2.0000	Fred	<b>1</b> .	Percent	Cum.	
0 1	2,57 1,51	71 LO	63.00 37.00	63.00 100.00	
Total	4,08	81	100.00		
. tab educd3					
edcat== 3.0000	Fred	4.	Percent	Cum.	
0 1	3,21 86	L4 57	78.76 21.24	78.76 100.00	
Total	4,08	81	100.00		

#### Construct indicator variables with xi



#### Construct interactions with xi

Cameron and Trivedi, op cit, p49 •

	xi	i.	edcat	*ear	nings	5,	noom	it	
i.	ede	cat	*earn	ri~s_	Īe	edo	xear	ni	#

(coded as above)

. summarize _I*

Variable	Obs	Mean	Std. Dev.	Min	Max
_Iedcat_1 _Iedcat_2 _Iedcat_3 _Iedcat_4 _IedcXearn~1	4081 4081 4081 4081 4081	. 2087724 . 3700074 . 2124479 . 2087724 3146. 368	.4064812 .4828655 .4090902 .4064812 8286.325	0 0 0 0	1 1 1 80000
_IedcXearn~2 _IedcXearn~3 _IedcXearn~4	4081 4081 4081	8757.823 6419.347 10383.11	15710.76 16453.14 32316.32	0 0 0	215000 270000 999999

### **Demeaning variables**

- . egen meanage = mean(age)
- . gen agedmean=age meanage
- . summarize age meanage agedmean

Max	Min	Std. Dev.	Mean	obs	Variable
50	30	5.650311	38. 37995	4290	age
38.37995	38. 37995	0	38. 37995	4290	meanage
11.62005	-8. 379953	5.650311	2. 32e-15	4290	agedmean

#### **Modeling and Graphing Interactions**

- Interactions are defined as the joint effect over and above the main effects.
- Therefore, both main effects must be in the model whether or not they are significant, to properly specify an interaction term.

#### When one variable is dummy-coded

 $y = a + b_1 x_1 + b_2 x_2 + b_3 x_1 x_2$  $y = 65 + 1.7 x_1 + 970 x_2 + -.5 x_1 x_2$ Case 1: assume  $x_2 = dummy$  variable for example : gender is coded 0 = male 1 = femalemale equation:  $y = 65 + 1.7 x_1 + 970 * 0 - .5 * 0$  $= 65 + 1.7 x_1$ female equation:  $y = (65 + 970 * 1) + (1.7 - .5 * 1)x_1$  $= 1635 + 1.2x_1$ 

# Stata commands for plotting the interaction

```
* Run a simple regression
label var y "academic achievement"
regresss v x1 x2
label var x1 "initial reading scores"
label var x2 "gender"
label define sx 0 "male" 1 "female"
label values x2 sx
* we construct an interaction term
gen x1Xx2 = x1*x2
label var x1Xx2 "interaction of x1 and x2"
* next we test it
regress v x1 x2 x1Xx2
* Now we construct an interaction graph
*********************************
* First we graph the main effects
graph twoway scatter y x1,title (Male acad achievement) || lfit y x1, title (The male equation)
graph twoway scatter y x_2 \parallel l lfit y x_2, title(The female equation)
We now solve for the interaction effect and generate it
replace Interact = 1635+1.2*x1
label var Interact "The Joint Effect over and above the main effects"
* Now we graph the interaction over and above the male and female effects
graph twoway scatter y x1 || lfitci y x1 || scatter y Interact || lfitci v Interact, ///
title(Interaction Graph betweeen males and females) ///
subtitle (Academic achievement as a function of initial reading scores) ///
caption (Male scores are blue while male and female scores interacting are orange)
```

```
Ready
```

# Interaction graph a non-crossed interaction


## Graphing the interaction

. tab gender							
gender	Freq.	Perce	nt Ci	um.			
male female	173 27	86. 13.	50 86 50 100	.50 .00			
Total	200	100.	00				
. tab gender,	nolabel						
gender	Freq.	Perce	nt Ci	um.			
0 1	173 27	86. 13.	50 86 50 100	.50 .00			
Total	200	100.	00				
. regress ach	n reading gende	r inter	act if gende	er==0 /	/male equation	ach= 5.2	+ 2*reading
Source	ss	df	MS		Number of obs	= 173	
Model Residual	6868443.74 65808.1601	1 171	6868443.74 384.843042		Prob > F R-squared	= 0.0000 = 0.9905 = 0.9905	
Total	6934251.9	172	40315.418		Root MSE	= 19.617	
ach	Coef.	Std. E	rr. t	P> t	[95% Conf.	Interval]	
reading gender interact cons	1.994127 (dropped) (dropped) 5.202285	.01492	68 133.59 39 1.74	0.000	1.964663	2.023592	
				0.001			

#### The male and female equations

. regress ach	reading gende	r inter	ract if ge	ender==0	<pre>//male equation</pre>	n ach= 5.2	+ 2*reading
Source	ss	df	MS		Number of obs	5 = 173	
Model Residual	6868443.74 65808.1601	1 171	6868443.7 384.84304	74 42	Prob > F R-squared	= 0.0000 = 0.9905 = 0.9905	
Total	6934251.9	172	40315.41	18	Root MSE	= 19.617	
ach	Coef.	Std. B	Err.	t P>	t  [95% Conf.	Interval]	
reading gender interact	1.994127 (dropped) (dropped)	.01492	268 133.	.59 0.0	00 1.964663	2.023592	
_cons	5.202285	2.995	339 1.	.74 0.0	847103167	11.11489	

end of do-file

do "C:\DOCUME~1\DRROBE~1.YAF\LOCALS~1\Temp\STD16000000.tmp"

regress ach reading gender interact //female equation ach = (5.2 + 58.4) + (2 + 5.9)*reading

Source	SS	df		MS		Number of obs	=	200
Model Residual	171960271 74703.4921	3 196	5732 381.	0090.3 140266		Prob > F R-squared	=	0.0000
Total	172034974	199	8644	97.359		Root MSE	=	19.523
ach	Coef.	Std. B	Err.	t	P> t	[95% Conf.	In	terval]
reading gender interact _cons	1.994127 58.41941 5.880514 5.202285	.0148 88.90 .2379 2.980	548 384 229 895	134.24 0.66 24.72 1.75	0.000 0.512 0.000 0.083	1.964831 -116.9115 5.411296 6764598	2 2 6 1	.023423 33.7503 .349731 1.08103

### Modeling the gender effects and its interaction

 Both equations can be inferred from the interaction model with its main effects included.

Male equation: Achievement = 5.2 + 2 * reading + gender + reading * gender if gender == 0= 5.2 + 2 * reading + 58.4 * 0 + 5.88 * reading *0= 5.2 + 2 * reading

*Female equation*:

Achievement = 5.2 + 2 * reading + 58.4 * 1 + 5.88 * reading * 1 if gender == 1 = (5.2+58.4) + 8 * reading

## Commands for generating the first order linear interaction graph



# Graph of the gender by reading interaction for academic achievement



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#### When 2 variables are continuous

- Split one at the mean.
- Cut it off 1 sd above and 1 sd below the mean.
- Run the regression for all three portions.
- You will get a different regression line for each
- Then plot those regression lines

### Modeling strategies

- Hierarchical regression (Jack and Pat Cohen popularized this approach sequential set inclusion, not multilevel modeling)
  - From specific to general
  - Two levels of analysis
- Stepwise regression

   Problems with it.

#### Sir David F. Hendry



- General-to-specific modeling
  - Specification error can bias results more than
    - multicollinearity
  - Avoidance of specification error

#### **Robust regression**

- Outlier diagnosis
  - Outlier downweighting
- White estimators
- Weighted Least Squares for heteroscedastic correction
- Median regression
- Quantile regression
- Bootstrapped regression for empirical standard errors

#### Halbert White Father of the Sandwich Variance (White) estimator

This variance estimator is robust to moderate violations of heteroscedasticity when the sample gets large.



## Robust regression with outlier downweighting

. rreg systolic drug1 drug2 drug4

```
Huber iteration 1: maximum difference in weights = .5
Huber iteration 2: maximum difference in weights = .04110695
Biweight iteration 3: maximum difference in weights = .15802154
Biweight iteration 4: maximum difference in weights = .00994916
```

Robust regression

Number of obs =	58
F(3, 54) =	10.19
Prob > F =	0.0000

systolic	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
drug1	18.71577	4.23037	4.42	0.000	10.23439	27.19715
drug2	18.40198	4.23037	4.35	0.000	9.9206	26.88336
drug4	5.524924	4.171201	1.32	0.191	-2.83783	13.88768
_cons	8.243576	3.153132	2.61	0.012	1.921928	14.56522

## Amount of weight given to an observation given distance t from mean of bandwidth



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## A Gaussian weight



#### Weighted Least squares regression

predict double olsres1, residual

generate double res1sq = olsres1^2

```
. * step two run the WLS
. regress systolic drug1 drug2 drug4 [aweight=1/res1sq], vce(robust)
(sum of wgt is 2.6759e+02)
```

Linear regression

obs	=	58
54)	=91	346.89
	=	0.0000
	=	0.9938
	=	.46126
	obs 54)	obs = 54) = <b>91</b> = = =

systolic	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
drug1	17.0113	.0325205	523.09	0.000	16.9461	17.0765
drug2	17.15796	.1953695	87.82	0.000	16.76627	17.54965
drug4	4.367606	.6461934	6.76	0.000	3.072066	5.663145
_cons	8.979034	.030306	296.28	0.000	8.918274	9.039794

## Robust regression (heteroscedastically consistent)

Using a sandwich estimator of the variance developed by Hal White in 1980, which is asymptotically heteroscedastically consistent

regress systolic drug1 drug2 drug4, robust

Linear regression

Number of	obs	=	58
F( 3,	54)	=	9.14
Prob > F		=	0.0001
R-squared		=	0.3355
ROOT MSE		=	10.721

systolic	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
drug1	17.31667	4.165217	4.16	0.000	8.965909	25.66742
drug2	16.78333	4.154201	4.04	0.000	8.454663	25.112
drug4	4.75	3.702364	1.28	0.205	-2.672792	12.17279
_cons	8.75	2.869919	3.05	0.004	2.99616	14.50384

. predict residrobust, residual

. jb residrobust Jarque-Bera normality test: **2.211** Chi(**2**) **.331** Jarque-Bera test for Ho: normality:

#### **Median regression**

predicts the 50th percentile of the dependent variable

. webuse auto (1978 Automob	ile Data)					
. qreg mpg pr Iteration 1:	ice weight lo WLS sum of	ength weighted de	viations =	168.24809		
Iteration 1: Iteration 2: Iteration 3: Iteration 4: Iteration 5: Iteration 6:	sum of abs. sum of abs. sum of abs. sum of abs. sum of abs. sum of abs.	weighted de weighted de weighted de weighted de weighted de weighted de	viations = viations = viations = viations = viations = viations =	167.8881 164.9883 164.77884 164.47639 164.08687 164.08685		
Median regres Raw sum of Min sum of	sion deviations deviations <b>1</b> 0	328 (abo 64.0869	ut <b>20</b> )	Number Pseudo	of obs = R2 =	74 0.4997
mpg	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
price weight length _cons	0001344 0040629 033546 40.07593	.0001665 .0017853 .0583821 6.381075	-0.81 -2.28 -0.57 6.28	0.422 0.026 0.567 0.000 2	0004664 0076236 1499854 27.34928	.0001976 0005022 .0828934 52.80258

#### Variance weighted least squares regression for severe heteroscedasticity Stata Reference Guide Q-Z(2007), pp 554-559.

- Mediated					And Address	
Total	400	100.00				
. regress bp g	gender race					
Source	55	df	MS	N	umber of obs	= 400
Model Residual	4485.66639 58442.7305	2 2242 397 147.	2.83319 210908	P	rob > F -squared	= 0.0000 = 0.0713 = 0.0666
Total	62928.3969	399 157	.71528	R	oot MSE	= 12.133
bp	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
gender race _cons	6.1775 2.5875 116.4862	1.213305 1.213305 1.050753	5.09 2.13 110.86	0.000 0.034 0.000	3.792194 .2021938 114.4205	8.562806 4.972806 118.552
. predict res1 . sktest(res1)	L, residual )					
	Skewness	/Kurtosis t	ests for	Normality	icint	
variable	Pr(Skewness	) Pr(Kurt	osis) ad	dj chi2(2)	Prob>chi	2
res1	0.012	0.97	4	6.19	0.0452	-
. hettest res1	L					
Breusch-Pagan Ho: C Varia	/ Cook-Weisbe Constant varia ables: res1	rg test for nce	heterosi	kedasticit	у	
chi2( Prob	(1) = > chi2 = 0	18.87 .0000				

#### **Graphical diagnosis**



predict res, residual

predict xb (option xb assumed; fitted values)

scatter res xb

#### Weighting the variables by inverting s²

- Stata can weight each variable xi by its variance, thus normalizing the effect of the variable by its spread across the line of estimation (prediction).
- Thus, heteroscedasticity is automatically corrected for by this procedure.

 $V = diagonal(s_1^2, s_2^2, ..., s_k^2)$ where

k = number of variables (not including the constant)  $s_k = std$  deviation of variable k  $b = (X'V^{-1}X)^{-1}(X'V^{-1}Y)$ Goodness of fit  $\chi^2_{n-k} = (y - Xb)V^{-1}(y - Xb)$ 

#### Stata command: vwls

. vwls bp gender race

Variance-weigł Goodness-of-fi Prob > chi2	nted least-squ it chi2( <b>1</b> )	uares regres = 0.88 = 0.3486	sion	Nu Mo Pr	mber of obs del chi2( <b>2</b> ) ob > chi2	= 400 = 27.11 = 0.0000
bp	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
gender race _cons	5.876522 2.372818 116.6486	1.170241 1.191683 .9296297	5.02 1.99 125.48	0.000 0.046 0.000	3.582892 .0371631 114.8266	8.170151 4.708473 118.4707

Bootstrap Methods (Efron, B.) Cameron and Trivedi, 417.

- Resampling methods.
  - Saving the means for repeated samples.
  - Obtain a sampling distribution of means.

With 400 samples, B = 400.

$$\overline{\hat{\theta}}^* = \frac{\sum_{b=1}^{B} \hat{\theta}_b^*}{B} = mean of bootstrap$$

$$Var(\theta_{boot}) = \frac{\sum_{b=1}^{B} (\hat{\theta}_{b}^{*} - \overline{\hat{\theta}}^{*})^{2}}{B - 1}$$

 $SE_{boot} = \sqrt{Var(\theta_{boot})}$  Robert Alan Yaffee, Ph.D.

# Bradley Efron (Stanford University developed bootstrapping



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#### **Bootstrap confidence intervals**

95% confidence intervals

**95%** confidence intervals =  $\hat{\theta}_b^* \pm 1.96 \sqrt{Var_{boot}}$ 

#### Bootstrap estimate of bias

• Suppose that the  $\hat{O}$  estimator of  $\theta$  is biased:

bias =  $\overline{\hat{\theta}_b}^* - \hat{\theta}$ where  $\hat{\theta} = DGP$  value  $\overline{\hat{\theta}_b}^* = mean of the estimator, given the DGP value$ 

#### How many bootstraps are needed?

- Efron and Tibshirani(1993), B=50 is good enough and very seldom are more than 200 needed.
- Cameron and Trivedi suggest 400. When I read Efron, I recall the number 10000 seems to be the number of replications needed.

#### **Bootstrapped Regression**

. bootstrap, nodots reps(1000) bca: regress mpg weight foreign wt2

Linear regression

Number of obs	=	74
Replications	=	1000
wald chi2( <b>3</b> )	=	167.54
Prob > chi2	=	0.0000
R-squared	=	0.6913
Adj R-squared	=	0.6781
ROOT MSE	=	3.2827

mpg	Observed Coef.	Bootstrap Std. Err.	z	P> z	Normal [95% Conf.	-based Interval]
weight	0165729	.0037912	-4.37	0.000	0240036	0091423
foreign	-2.2035	1.064398	-2.07	0.038	-4.289683	1173179
wt2	1.59e-06	5.91e-07	2.69	0.007	4.33e-07	2.75e-06
_cons	56.53884	5.982533	9.45	0.000	44.81329	68.26439

#### **BCA** option

- Bias correction: Corrects for bias in the bootstrap.
- Acceleration: allows for more asymmetric distributions.

#### Poisson count models

- "Much of the world is distributed lognormally," E. Tufte.
  - when the dependent variable is an integer or a rare event.
  - Disadvantage with this model is that it assumes that the mean= variance.

Poisson model :

 $\mu = e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p)} \quad or \quad \ln(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p$ 

Poisson distribution:

$$Prob(y | \mu) = \frac{e^{-\mu} \mu^{y}}{y!}, \quad for \ y = 0, 1, 2, ...$$

#### where

 $\mu = expected \ count \qquad and \ \mu \ is \ called \ the \ rate \ parameter \\ and \ when \ dealing \ with \ l \ time \ frame \ (the \ predicted \ \# \ events) \\ y = observed \ count \\ assumes \ \mu > 0, \\ \mu = mean = variance.$ 

#### Poisson regression model

 named after Simeon–Denis Poisson, who discovered the distribution on which this was based.

> Poisson regression standard model : ln(E(Y)) = a + bx + e



Poisson regression

rate model :  $ln(E(Y)) - ln(exposure) = ln\left(\frac{E(Y)}{exposure}\right) = a + bx$  $ln(E(Y)) = ln(exposure) + ln\left(\frac{E(Y)}{exposure}\right) = a + bx$ 

The offset

#### Poisson count models

. webuse airl	ine					
. poisson injuries XYZowned, exposure(n)						
Iteration 0: log likelihood = -23.027197 Iteration 1: log likelihood = -23.027177 Iteration 2: log likelihood = -23.027177						
Poisson regression			Numbe	rofobs =	9	
Log likelihood = - <b>23.027177</b>			Prob Pseud	> chi2 = > chi2 = 0 R2 =	0.1836 0.0370	
injuries	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
XYZowned _cons n	.3808084 4.061204 (exposure)	.2780192 .147442	1.37 27.54	0.171 0.000	1640993 3.772223	.9257161 4.350185
. gen lnN=ln(n . poisson injo	n) uries XYZowneo	1 lnN				
Iteration 0: log likelihood = -22.333874 Iteration 1: log likelihood = -22.332275 Iteration 2: log likelihood = -22.332275						
Poisson regression Log likelihood = - <b>22.332275</b>			Numbe LR ch Prob Pseud	r of obs = i2(2) = > chi2 = o R2 =	9 19.15 0.0001 0.3001	
injuries	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
XYZowned lnN _cons	.6840667 1.424169 4.863891	. 3895877 . 3725155 . 7090501	1.76 3.82 6.86	0.079 0.000 0.000	0795111 .6940517 3.474178	1.447644 2.154286 6.253604

## **Comparing Poisson models**

Log likelihood	d = - <b>1742.573</b> 9	5		LR ch Prob Pseud	i2( <b>0</b> ) > chi2 o R2	= 0.00 = . = 0.0000
art	Coef.	Std. Err.	z	P> z	[95% Con	f. Interval]
_cons	.5264408	.0254082	20.72	0.000	.4766416	.57624
. est store nu	u11					
. poisson art	fem-ment					
Iteration 0: Iteration 1: Iteration 2: Iteration 3:	log likelind log likelind log likelind log likelind	d = -1651. d = -1651. d = -1651. d = -1651. d = -1651.	4574 0567 0563 0563			
Poisson regree	ssion d = - <b>1651.056</b> 3	3		Numbe LR ch Prob Pseud	r of obs i2( <b>5</b> ) > chi2 o R2	= 915 = 183.03 = 0.0000 = 0.0525
art	Coef.	Std. Err.	z	P> z	[95% Con	f. Interval]
fem mar kid5 phd ment _cons kid5 phd ment _cons	2245942 .1552434 1848827 .0128226 .0255427 .3046168 1848827 .0128226 .0255427 .3046168	.0546138 .0613747 .0401272 .0263972 .0020061 .1029822 .0401272 .0263972 .0020061 .1029822	-4.11 2.53 -4.61 0.49 12.73 2.96 -4.61 0.49 12.73 2.96	0.000 0.011 0.000 0.627 0.000 0.003 0.000 0.627 0.000 0.627 0.000	3316352 .0349512 2635305 038915 .0216109 .1027755 2635305 038915 .0216109 .1027755	1175532 .2755356 1062349 .0645601 .0294746 .5064581 1062349 .0645601 .0294746 .5064581
. est store fo . lrtest null	ull full					
Likelihood-rat (Assumption:	tio test null nested in	n full)	@2000.F		LR chi2( <b>5</b> ) Prob > chi2	= 183.03 = 0.0000

#### **Poisson model assumptions**

- Observations are independent
- Measures integers (counts) of events
- No multicollinearity
- Residuals are skewed; in OLS they are symmetric.
- Variance increases as the mean increases whereas in traditional regression models the variance is constant.
- Overdispersion (the variance is larger than the mean) for any number of cases does not exist.
  - If it occurs, there are corrections for it that can be applied as in the next model we discuss.

#### Test for overdispersion

Cameron and Trivedi Microeconomics using Stata (p.561)

- Overdispersion is where the conditional variance is greater than the conditional mean.
- If you have a random variable with measurement error, v, you could have an error such as uv instead of just u. If E(v)=1, it would preserve the mean but increase the variance (for logged dependent variables).
- $E(y)=\mu$ ,  $Var(y)=\mu(1+\mu\sigma^2)$

#### Test for Overdispersion--continued

- Test = if  $x = (resid^2 dv)/dv$
- We regress dv on x, and if it is significant, there is overdispersion.
- If p(b) < 0.05, then we use the negative binomial model.

### Negative binomial Models nbreg models

- Also used for count data
- The mean does not have to equal the variance
  - Stata has this for zero-inflated and regular
  - It has it in the complex survey module as well as in the regular options.
  - It fits both the Poisson and the Negative binomial regression.
- A Poisson likelihood with a gamma prior (for all the Bayesians)

#### Assumptions of the negative binomial

- no multicollinearity
- Overdispersion is permitted here
- The Poisson parameter is itself a gamma distribution.

#### **Binary dependent variable models**

#### The probit regression model

 Assumes an underlying latent variable that is normally distributed. The proportions determine the cut-point in the normal distribution. If the value is greater than the cut-point, the respondent gets a 1, otherwise his value is scored as a zero.

#### The logistic regression model

- Uses the natural log of the odds ratio (the logit) as the dependent variable.
- Odds ratio = prob(event)/(1-prob(event))
#### Logistic regression

Formula for logistic regression:

Regression models for binary dependent variables

 $odds = \frac{prob}{1 - prob}$   $odds = e^{(a+b_1x_1+b_2x_2+...+b_px_p)}$  logit = ln(odds) $logit = a + b_1x_1 + b_2x_2 + ... + b_px_p$ 

#### Converting an odds to a probability

- Odds= prob/(1-prob)
- Odds(1-prob)=prob
- Odds- Odds*prob= prob
- Prob = Odds/(1+Odds)
- Prob = e^(X'B)/[1+ e^(X'B)]
- Prob =  $e^{(a + b_1x_1 + ...)/[1 + e^{(a + b_1x_1 + ...)]}$

### Cumulative Density Function of Logistic transformation

Plot[CDF[LogisticDistribution[0, 2], x], {x, -10, 10}]



### Logistic regression

. logistic low age smoke ht ui ftv, coef									
Logistic regression					Number of obs =				
Log likelihood	= - <b>109.0035</b>	L		Prob Pseud	> chi2 lo R2	=	0.0052		
low	Coef.	Std. Err.	z	P> z	[95% Con	nf.	Interval]		
age smoke ht ui ftv _cons	0440911 .6664874 1.400399 .9936605 0302462 3024128	.0338158 .3315275 .6278679 .4335712 .1627385 .7938149	-1.30 2.01 2.23 2.29 -0.19 -0.38	0.192 0.044 0.026 0.022 0.853 0.703	1103689 .0167055 .1698007 .1438766 3492078 -1.858262	) 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5	.0221867 1.316269 2.630998 1.843444 .2887154 1.253436		

lsens

. 1roc

Logistic model for low

number of	observations	=	189
area unde	er ROC curve	=	0.6870

# Converting coefficients to percentage change

Log likelihood	d = -109.020	9		Pseu	do R2 =	0.0709
low	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
age smoke ui ht _cons	0454688 .6685009 .9984597 1.411142 2966465	.032994 .3313015 .4324669 .6259552 .7925553	-1.38 2.02 2.31 2.25 -0.37	0.168 0.044 0.021 0.024 0.708	1101359 .0191618 .1508402 .1842924 -1.850026	.0191982 1.31784 1.846079 2.637992 1.256733
. listcoef, pe logistic (N=14 Odds of: 1 )	ercent // 0 89): Percentag /s O	computing th ge Change in	e percent Odds	change	in the odds	

1ow	b	z	P>   Z	96	%StdX	SDofX
age	-0.04547	-1.378	0.168	-4.4	-21.4	5.2987
smoke	0.66850	2.018	0.044	95.1	38.7	0.4894
ui	0.99846	2.309	0.021	171.4	42.7	0.3562
ht	1.41114	2.254	0.024	310.1	41.2	0.2445

#### Isens and Iroc





#### estat class and estat gof

estat clas

Logistic model for low

Classified	D D	~D	Total
+ -	13 46	10 120	23 166
Total	59	130	189

Classified + if predicted Pr(D) >= .5 True D defined as low != 0

Sensitivity	Pr(+ D)	22.03%
Specificity	Pr(- ~D)	92.31%
Positive predictive value	Pr(D +)	56.52%
Negative predictive value	Pr(~D -)	72.29%
False + rate for true ~D	Pr(+ ~D)	7.69%
False - rate for true D	Pr(-  D)	77.97%
False + rate for classified +	Pr(~D  +)	43.48%
False - rate for classified -	Pr(D  -)	27.71%
Correctly classified		70.37%

estat gof

Logistic model for low, goodness-of-fit test

number of observations =	189
number of covariate patterns =	118
Pearson chi2( <b>112</b> ) =	120.23
Prob > chi2 =	0.2806

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## Comparing nested models with information criteria

Logistic regre Log likelihood	ession d = - <b>46.94226</b>	5		Number LR chi Prob > Pseudo	of obs = 2(1) = chi2 = R2 =	112 61.24 0.0000 0.3948
status	Odds Ratio	Std. Err.	z	P> z	[95% Conf.	Interval]
mod1	3.57066	.7690696	5.91	0.000	2.341056	5.446095
. est store mo	od1 atus mod2					
Logistic regre Log likelihood	ession d = - <b>34.36010</b> 4	L		Number LR chi Prob > Pseudo	of obs = 2(1) = chi2 = R2 =	112 86.40 0.0000 0.5570
status	Odds Ratio	Std. Err.	z	P> z	[95% Conf.	Interval]
mod2	5.151567	1.413896	5.97	0.000	3.008286	8.821849
. est store mo . est stats _a	od2 all					
Model	0bs 11	(null) 11	(model)	df	AIC	BIC
mod1 mod2	112 -77 112 -77	.56104 -4 .56104 -	6.94226 34.3601	2 2	97.88452 72.72021	103.3215 78.15721
	Note: N=Obs	used in ca	lculating	BIC; see	[R] BIC not	e

#### **Information Criteria**

Information Criterion = deviance + penalty for number of parameters

-2LL ~ SSE (deviance)
AIC = -2LL + 2p
BIC = -2LL + plog(n)

### Receiver Operating Characteristic Analysis



### **Screening analysis**

. roctab disease rating, detail

#### Detailed report of Sensitivity and Specificity

LR-	LR+	Correctly Classified	Specificity	Sensitivity	Cutpoint
0.1034 0.1458 0.1769 0.3655 1.0000	1.0000 2.1835 2.7534 3.8492 18.7647	46.79% 74.31% 77.98% 81.65% 81.65% 53.21%	0.00% 56.90% 67.24% 77.59% 96.55% 100.00%	100.00% 94.12% 90.20% 86.27% 64.71% 0.00%	(>= 1) (>= 2) (>= 3) (>= 4) (>= 5) (> 5)

Obs	Area	Std. Err.	[95% Conf.	Interval]
109	0.8932	0.0307	0.83295	0.95339

# Comparison of ROC curves to compare logistic models

	. roccomp status	5 mod1 mod	2, graph su	ummary			
		Obs	ROC Area	Std. Err	-/ ·. [9	symptotic 5% Conf.	Normal— Interval]
	mod1 mod2	112 112	0.8828 0.9302	0.031 0.025	7 ( 5 (	). 82067 ). 88005	0.94498 0.98042
10.	Ho: area( <b>mod1</b> ) = chi2( <b>1</b> ) =	area(mod 2.31	<b>12)</b> Prob>cl	ni2 = <b>0.</b> 1	L282		
	🔟 Stata Graph - Gra	aph		•e - (			
	<u>File E</u> dit <u>O</u> bject	<u>G</u> raph <u>T</u> ools	<u>H</u> elp				
÷.			• F 2 4	. II. ▶			
1	🛄 Graph						
	22 100		•		-		
	ensitivity 0.50 0.50						
	0.25 8				_		
ff 1	8.				_		
1	0.00 0	.25 1-S	0.50 Specificity	0.75	1.00		
di.	mod1 Refere	ROC area: 0.88	28 — • moo	2 ROC area: 0.93	302		

### Logistic regression

. logit low sm	noke ui ht						
Iteration 0: Iteration 1: Iteration 2: Iteration 3:	log likeliho log likeliho log likeliho log likeliho	pod = -117 pod = -110.07 pod = -110.07 pod = -110.07 pod = -110.07	. 336 7602 0286 0285				
Logistic regression Log likelihood = - <b>110.00285</b>				Numbe LR ch Prob Pseud	r of obs i2( <b>3</b> ) > chi2 o R2	= = =	189 14.67 0.0021 0.0625
low	Coef.	Std. Err.	z	P> z	[95% C	onf.	Interval]
smoke ui ht _cons	.6831291 1.038394 1.417422 -1.355087	. 3292861 . 4279777 . 6235288 . 2414971	2.07 2.43 2.27 -5.61	0.038 0.015 0.023 0.000	.03774 .19957 .19532 -1.8284	03 35 83 12	1.328518 1.877215 2.639516 8817612

### Testing multiple coefficients

. test	smoke = ui	
(1)	smoke – ui = O	
	chi2( 1) = Prob > chi2 =	0.43 0.5121
. test	smoke ui	
(1) (2)	smoke = 0 ui = 0	
	chi2( 2) = Prob > chi2 =	10.27 0.0059

#### Logistic regression postestimation

#### estat gof

Logistic model for low, goodness-	<u>-of-fit test</u>
number of observations =	189
number of covariate patterns =	0.67
Prob > chi2 =	0.7169

#### estat class

#### Logistic model for low

classified	True - D	~D	Total
+ -	14 45	11 119	25 164
Total	59	130	189

Classified + if predicted Pr(D) >= .5 True D defined as low != 0

Sensitivity	Pr( +  D)	23.73%
Specificity	Pr( - ~D)	91.54%
Positive predictive value	Pr( D  +)	56.00%
Negative predictive value	Pr(~D  -)	72.56%
False + rate for true ~D	Pr(+ ~D)	8.46%
False - rate for true D	Pr(-  D)	76.27%
False + rate for classified +	Pr(~D  +)	44.00%
False - rate for classified -	Pr(D  -)	27.44%
Correctly classified		

#### Fitstat, save

. logistic low	v age smoke ui	i ht, coef					
Logistic regression				Numbe LR ch Prob	er of obs ni2( <b>4</b> ) > chi2	= = =	189 16.63 0.0023
Log likelihood	d = -109.0209	9		Pseud	do R2	=	0.0709
low	Coef.	Std. Err.	z	P> z	[95% (	conf.	Interval]
age smoke ui ht _cons	0454688 .6685009 .9984597 1.411142 2966465	.032994 .3313015 .4324669 .6259552 .7925553	-1.38 2.02 2.31 2.25 -0.37	0.168 0.044 0.021 0.024 0.708	1101 .0191 .1508 .1842 -1.850	359 618 402 924 026	.0191982 1.31784 1.846079 2.637992 1.256733

. fitstat, save

#### Measures of Fit for logistic of low

Log-Lik Intercept Only:	-117.336	Log-Lik Full Model:	-109.021
D(184):	218.042	LR(4):	16.630
		Prob > LR:	0.002
McFadden's R2:	0.071	McFadden's Adj R2:	0.028
Maximum Likelihood R2:	0.084	Cragg & Uhler's R2:	0.118
McKelvey and Zavoina's R2:	0.114	Efron's R2:	0.084
Variance of y*:	3.714	Variance of error:	3.290
Count R2:	0.704	Adj Count R2:	0.051
AIC:	1.207	AIC*n:	228.042
BIC:	-746.440	BIC':	4.337

(Indices saved in matrix fs_0)

#### Formulae for fitstats

Likelihood ratio  $\chi^2 = 2Ln(Full model) - 2ln(null model) df = diff in parms$ Deviance = -2lnL(Full Model) df = N - parms

$$R^{2} = \frac{Var(\hat{y})}{Var(\hat{y}) + Var(\hat{\varepsilon})} = 1 - \left(\frac{L(\text{mod }null)}{L(\text{mod }full)}\right)^{2/N}$$
  
adj  $R^{2} = \left(R^{2} - \frac{p}{N-1}\right)\left(\frac{N-1}{N-p-1}\right)$  where  $p = number of parameters$ 

N = number of observations.

McFadden's  $R^2 = 1 - \frac{LL(mod full)}{LL(mod null)}$  always increases with addition of variables.

Maximum likelihood (Cox - Snell)  $R^2$ 

$$= \mathbf{1} - \left(\frac{L(\text{mod } null)}{L(\text{mod } full)}\right)^{2/N} = \mathbf{1} - \exp(-G^2/N)$$

Cragg & Uhler's (Nagelkerke)  $R^2 = \frac{R_{ML}^2}{\max R_{ML}^2}$ 

$$\frac{\left(1 - \left\{L(Modnull / LModfull\right\}\right)^{2/N}}{1 - L(Modnull)^{2/N}}$$

=

#### More Fitstat

*Efron's pseudo*  $R^2$  *for binary outcomes defines*  $\hat{y} = \hat{\pi} = \Pr(y = I | x)$ 

$$= \mathbf{1} - \frac{\sum_{i=1}^{N} (y_i - \hat{\pi}_i)^2}{\sum_{i=1}^{N} (y_i - \overline{y})^2}$$

Count  $R^2$  = measure of proportion of correct predictions =  $\frac{\sum n_{jj}}{N}$ .

Adjusted Count 
$$R^2 = \frac{\sum n_{jj} - \max(n_{r+})}{N - \max(n_{r+})}$$

Information criteria

 $AIC = -2LL(Model with k parms) - 2P_k$ 

 $AIC' = \frac{-2LL - 2P}{N}$ 

 $BIC = -2LL = dfk * \ln(N)$  where dfk = df of deviance(-2LL)

 $BIC' = -G^{2}(Model with k parms) - df'Ln(N) where df' = \# regressors in model$   $BIC^{s} = -2L * N * Ln(Model with k parms) + dfksln(N) where dfks = \# parms in model$ including the constant.

#### More fitstat

 Source of fitstat info: Long and Reese, op. cit., pp. 107-111.

McKelvey & Zavoina's  $R^2 = \frac{Var(y^*)}{Var(y^*) + Var(e)}$ 

where

 $y^* = latent variable.$ 

#### **ROC curve**





## Save and analyze predicted probabilities of outcome

#### Command: predict prvalue, pr

. oneway p	prva	lue ra	ce, tai	pulate	SIDAK				
rac	e		Summa Mean	ary of Std.	Pr(low) Dev.	) Fre	eq.		
whit blac othe	:e :k ≌r	. 25 . 32 . 39	222338 973504 124544	.142 .141 .153	02386 15673 05018		96 26 67		
Tota	al	. 31	2 <b>169</b> 31	.158	65651	1	189		
Source	2		Ana SS	alysis	of Vart df	iance MS		F	Prob > F
Between gr Within gr	oup	is is	.771953 3.96030	3121 5196	2 186	.38597 .021297	7656 2269	18.13	0.0000
Total			4.7323	L508	188	.02517	1889		
Bartlett's	5 te	st for	equal v	/arian	ces: cł	ni2( <b>2</b> ) =	- 0.	<b>4958</b> Pro	b>chi2 = <b>0.780</b>
			Cor	nparis	on of Pr (Sida	·(low) H ak)	by rac	e	
Row Mean- Col Mean		whit	te	black					
black		.0775	12 51						
other		.1390	22 .	06151					

#### Storing results for model comparison

log likelihood = Iteration 0: -117.336 Iteration 1: log likelihood = -109.9783 log likelihood = -109.969 Iteration 2: Iteration 3: log likelihood = -109.969 Probit regression Number of obs = 189 LR chi2(3) 14.73 = Prob > chi20.0021 = Log likelihood = -109.969 Pseudo R2 0.0628 low coef. Std. Err. z P>|z| [95% Conf. Interval] .4137063 .1977981 2.09 0.036 .0260291 .8013835 smoke .2632082 2.42 0.016 .1206624 1.15242 ui .6365411 ht .8691405 .3826819 2.27 0.023 .1190978 1.619183 _cons -. 8285056 -5.91 -1.103421 .1402654 0.000 -. 5535905 est store probit logit low smoke ui ht Iteration 0: log likelihood = -117.336 Iteration 1: log likelihood = -110.07602 Iteration 2: log likelihood = -110.00286 Iteration 3: log likelihood = -110.00285 Logistic regression Number of obs 189 = LR chi2(3)14.67 = Prob > chi20.0021 Pseudo R2 Log likelihood = -110.00285 0.0625 low. Coef. Std. Err. P> | Z | [95% Conf. Interval] z smoke .6831291 . 3292861 2.07 0.038 .0377403 1.328518 1.877215 .4279777 0.015 .1995735 ui 1.038394 2.43 0.023 ht 1.417422 . 6235288 2.27 .1953283 2.639516 _cons -1.355087 .2414971 -5.61 -1.828412 -.8817612 0.000

est store logit

# Assumptions of binary logistic regression

- Linearity: The model is linear for logits.
- Additivity: There are no significant interactions.
- The residuals are binomially distributed until the sample size gets large when the binomial assumes a normal shape. Therefore, large samples are necessary for such Maximum likelihood estimation.
- No multicollinearity.
- No overly influential observations (Daniel Pregebon)

# Model Validation by testing assumptions

- Test each assumption to be sure it holds for the model. Check the sample size to be sure that it is large.
- Check for multicollinearity with the iv corr matrix.
- Test for interactions between variables.
- Plot the probabilities to check for linearity.

## Validating tests

- Check the Classification chart to be sure that the percentage correctly classified is high.
- Test for predictive validity of classification on an out-ofsample analysis. You can use Brier's Score = Error variance (with n as denominator). Nonparametric correlation between observed and predicted scores (Somer's D) should be high.
- Bootstrap or jacknife to be sure that the empirical std errors do not deviate much from those estimated.
- Compute the Q (the overall quality index). Q = D-U,
  - where D=discrimination score (LR chi-square-1)/n and the U = unreliability index ( 2LL between uncalibrated XB and the calibrated XB (with overall intercept and slope calibrated to the test sample).

#### Model comparison tables

est table logit probit, b(%9.3f) label varwidth(30) star(.1 .05 .01)

Variable	logit	probit
smoked during pregnancy	0.683**	0.414**
presence, uterine irritability	1.038**	0.637**
has history of hypertension	1.417**	0.869**
Constant	-1.355***	-0.829***

legend: * p<.1; ** p<.05; *** p<.01

. est table logit probit, b(%9.3f) label t varwidth(30)

Variable	logit	probit
smoked during pregnancy presence, uterine irritability has history of hypertension Constant	0.683 2.07 1.038 2.43 1.417 2.27 -1.355 -5.61	0.414 2.09 0.637 2.42 0.869 2.27 -0.829 -5.91

legend: b/t

#### Other model comparison tables

. estimates table logistic probit, b(%9.3f) star(.1 .05 .01) stats(ll aic bic) ///
> title(Comparison of full models)

Comparison of full models

Variable	logistic	probit
age	-0.045	-0.029
smoke	0.669**	0.409**
ui	0.998**	0.612**
ht	1.411**	0.861**
_cons	-0.297	-0.160
ll	-109.021	-108.882
aic	228.042	227.765
bic	244.251	243.974

legend: * p<.1; ** p<.05; *** p<.01

. estimates table probit logistic. b(%9.3f) t p stats(ll aic bic) title(Comparison of full models)

Comparison of full models

Variable	probit	logistic
age	-0.029	-0.045
smoke	0.1459	0.1682
ui	0.0396	2.02 0.0436 0.998
	2.31 0.0208	2.31 0.0210
ht	0.861 2.26	1.411 2.25
_cons	-0.160	-0.297
	0.7371	0.7082
ll aic bic	-108.882 227.765 243.974	-109.021 228.042 244.251

legend: b/t/p

## Model comparison with information criteria

. est stats _a	a]]					
Model	Obs	11(null)	ll(model)	df	AIC	BIC
probit logit	189 189	-117.336 -117.336	-109.969 -110.0029	4 4	227.938 228.0057	240.905 240.9727
	Note: N	⊫Obs used in	n calculating	g BIC; se	e [R] BIC no	te

Probit regression model introduced by Chester Ittner Bliss (1935)

It assumes that the underlying area of the normal curve is bifurcated so the proportions of counts in one group and those in the other represent the percentages of counts in the Os and 1s.
 lim Prob(Y = 1/x) = 1

 $x'\beta \rightarrow \infty$ 

 $\lim_{x'\beta\to-\infty} Prob(Y=1/x)=0$ 

Prob  $(Y = 1/x) = \int \phi(t)dt = \Theta(x'\beta)$ 

## Probit model

_	-						
二十三日に見る	. probit low s	smoke ui ht					
「北山山山」	Iteration 0: Iteration 1: Iteration 2: Iteration 3:	log likelih log likelih log likelih log likelih	bod = -117 bod = -109 bod = -109 bod = -109 bod = -109	. 336 9783 . 969 . 969			
北京市市大学生	Probit regress Log likelihood	sion d = - <b>109.96</b>	9		Numbe LR ch Prob Pseud	r of obs = i2(3) = > chi2 = o R2 =	189 14.73 0.0021 0.0628
a la la	low	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
北京加加	smoke ui ht _cons	.4137063 .6365411 .8691405 8285056	.1977981 .2632082 .3826819 .1402654	2.09 2.42 2.27 -5.91	0.036 0.016 0.023 0.000	.0260291 .1206624 .1190978 -1.103421	.8013835 1.15242 1.619183 5535905
	. estat gof Probit model for low. goodness-of-fit test						
夏季は日日田	number of observations = 189 number of covariate patterns = 6 Pearson chi2(2) = 0.60 Prob > chi2 = 0.7419						
	. estat class						

## An assumption of an underlying normal variable



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#### **Classification table**

. estat class

Probit model for low

classified	True -		Total
Classified	U	~0	TOLAT
+	14	11	25
-	45	119	164
Total	59	130	189

Classified + if predicted Pr(D) >= .5 True D defined as low != 0

Sensitivity	Pr( +  D)	23.73%
Specificity	Pr( - ~D)	91.54%
Positive predictive value	Pr( D  +)	56.00%
Negative predictive value	Pr(~D  -)	72.56%
False + rate for true ~D	Pr( + ~D)	8.46%
False - rate for true D	Pr( -  D)	76.27%
False + rate for classified +	Pr(~D  +)	44.00%
False - rate for classified -	Pr( D  -)	27.44%
Correctly classified		70.37%

#### Fitstat, diff force

Probit regression Log likelihood = <b>-108.88245</b>				Numbe LR ch Prob Pseud	er of obs = hi2(4) = > chi2 = lo R2 =	189 16.91 0.0020 0.0720
low	Coef.	Std. Err.	z	P> z	[95% Conf	Interval]
age smoke ui ht _cons	0288735 .4087187 .6118533 .8608394 1600211	.0198574 .1986022 .2647648 .3808234 .4766837	-1.45 2.06 2.31 2.26 -0.34	0.146 0.040 0.021 0.024 0.737	0677934 .0194654 .0929238 .1144392 -1.094304	.0100463 .7979719 1.130783 1.60724 .7742617

. fitstat, force diff

Measures of Fit for probit of low

Warning: Current model estimated by probit, but saved model estimated by logistic

Model:	Current probit	Saved logistic	Difference
N:	189	189	0
Log-Lik Intercept Only:	-117.336	-117.336	0.000
Log-Lik Full Model:	-108.882	-109.021	0.138
D:	217.765(184)	218.042(184)	<b>0.277</b> (0)
LR:	16.907(4)	16.630(4)	0.277(0)
Prob > LR:	0.002	0.002	
McFadden's R2:	0.072	0.071	0.001
McFadden's Adj R2:	0.029	0.028	0.001
Maximum Likelihood R2:	0.086	0.084	0.001
Cragg & Uhler's R2:	0.120	0.118	0.002
McKelvey and Zavoina's R2:	0.138	0.114	0.024
Efron's R2:	0.085	0.084	0.001
Variance of y*:	1.161	3.714	-2.553
Variance of error:	1.000	3.290	-2.290
Count R2:	0.704	0.704	0.000
Adj Count R2:	0.051	0.051	0.000
AIC:	1.205	1.207	-0.001
AIC*n:	227.765	228.042	-0.277
BIC:	-746.717	-746.440	-0.277
BIC':	4.060	4.337	-0.277

Difference of 0.277 in BIC' provides weak support for current model.

Note: p-value for difference in LR is only valid if models are nested.

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### Receiver Operating Characteristic Curve



Stata postestimation command: Inoc Yaffee, Ph.D.

#### Stata Postestimation command: Isens


Regression analysis for Ordinal Dependent Variables

 Ordinal logistic regression using cumulative logits

Ordinal probit regression

## **Ordinal logistic regression**

- Is the dependent variable an ordered typology? Is it actually an ordered variable?
- Ordinal logistic regression uses cumulative logits.
- Several cutpoints split the dependent variable into a reference set and the remainder for comparison with the reference set. These cutpoint usually increase with the number of levels in the dependent variable.
- There are # levels minus 1 cutpoints for the dependent variable.

## **Cumulative logits**

 Suppose a dependent variable has three ordered categories: low, medium, and high.



## **Cumulative logits**

 Logit 1 uses cutpoint 1 to divide the sets into probability 1 and 1- probability 1.



Logit1 = ln(p/(1-p))

## **Cumulative logits**

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## Logit 2 uses cutpoint 2 to divide the sets into probability 2 and 1- probability 2.



Logit2 = ln(prob 2/(1-prob2)

## Assumptions of the ordinal logistic regression model

- Logits (In(odds)) are linearly related to the predictors, such that an ordered structure of response (is preserved without necessarily revealing the precise extent of this ordering) of the dependent variable is maintained with respect to each predictor variable.
- Linearity and additivity: Regression coefficients are independent of the cut-point for the level of Y employed. This prevents any interaction between the X variables from being significant.
- Additivity: Proportional odds assumption( parallel regression assumption) holds: There are no significant interactions among independent variables. If interactions were significant, then there would be valid nonlinear or multiplicative effects.

### Formulation of this assumption

• Assume that the cutpoints are represented by  $\tau 1, \tau 2, \text{ and } \tau 3$ . The response variable measure low, medium, and high satisfaction wrt a treatment.  $\Pr(\gamma \le 1 | x) = F(\tau_1 - \beta x)$ 

F=cumulative probability density function.  $Pr(y \le 1 \mid x) = F(\tau_1 - \beta x)$   $Pr(y \le 2 \mid x) = F(\tau_2 - \beta x)$   $Pr(y \le 3 \mid x) = F(\tau_3 - \beta x)$   $\vdots$   $Pr(y \le J \mid x) = F(\tau_i - \beta x)$ 

### Stata's estimate

Model parameter	Stata estimate	different Parameter- ization	
β ₀	B ₀ - B ₀ =0	Β ₀ - τ ₁	
τ ₁	$\tau_1$ - $B_0$	$\tau_1$ - $\tau_1$ =0	
τ ₂	$\tau_2$ - $B_0$	$\tau_2$ - $\tau_1$	
τ ₃	$\tau_3$ - $B_0$	$\tau_3$ - $\tau_1$	

J. Scott Long and Jeremy Freese ,2nd ed., 2006, p.196 Tau values are the cutpoints

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# The Brant test of this assumption significant result=> violation of || odds

orogic warm	yr os mare win	ice age eu pi	50, 1010	9			
ordered logist .og likelihood	tic regression d = - <b>2844.912</b> 3	1 3		Numbe LR ch Prob Pseud	r of obs i2( <b>6</b> ) > chi2 o R2	= = =	2293 301.72 0.0000 0.0504
warm	Coef.	Std. Err.	z	P> z	[95% Cor	nf.	Interval]
yr89 male white age ed prst	.5239025 7332997 3911595 0216655 .0671728 .0060727	.0798988 .0784827 .1183808 .0024683 .015975 .0032929	6.56 -9.34 -3.30 -8.78 4.20 1.84	0.000 0.000 0.001 0.000 0.000 0.000	.3673037 8871229 6231819 0265032 .0358624 0003813	7 9 5 2 4 3	.6805013 5794766 1591374 0168278 .0984831 .0125267
/cut1 /cut2 /cut3	-2.465362 630904 1.261854	.2389126 .2333155 .2340179			-2.933622 -1.088194 .8031873	2 4 3	-1.997102 173614 1.720521

brant, detail

Estimated coefficients from j-1 binary regressions

warm vr80 male white age of pret

	y>1	y>2	y>3
yr 89	.9647422	.56540626	.31907316
male	30536425	6905 4232	-1.0837888
white	55265759	31427081	39299842
age	0164704	02533448	01859051
ed	.10479624	.05285265	.05755466
prst	00141118	.00953216	.00553043
_cons	1.8584045	.73032873	-1.0245168

Brant Test of Parallel Regression Assumption

Variable	chi2	p>chi2	df	
A11	49.18	0.000	12	
yr 89	13.01	0.001	2	
male	22.24	0.000	2	
white	1.27	0.531	2	
age	7.38	0.025	2	
ed	4.31	0.116	2	
prst	<b>4.33</b> COD	vright @2	2003	Robert Alan Yaffee

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## Graphical test of the Proportional Odds assumptions



#### tests for proportionial odds assumption



## **Ordinal logistic regression**

-	-	h.	100	~	-	7	7
L .	dl			e	D	1	/

Record 1977	Freq.	Percent	Cum.
Poor Fair Average Good Excellent	3 11 27 20 5	4.55 16.67 40.91 30.30 7.58	4.55 21.21 62.12 92.42 100.00
Total	66	100.00	

. ologit rep77 foreign length mpg rseat

Iteration 0: log likelihood = -89.895098Iteration 1: log likelihood = -76.920557Iteration 2: log likelihood = -76.245131Iteration 3: log likelihood = -76.234642Iteration 4: log likelihood = -76.234635

```
Ordered logistic regression
```

Log likelihood = -76.234635

Number of obs	=	66
LR chi2( <b>4</b> )	=	27.32
Prob > chi2	=	0.0000
Pseudo R2	=	0.1520

rep77	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
foreign length mpg rseat	3.277431 .1066986 .2355305 2093045	.8354878 .0263115 .0717607 .1067571	3.92 4.06 3.28 -1.96	0.000 0.000 0.001 0.050	1.639905 .055129 .094882 4185446	4.914957 .1582681 .376179 0000644
/cut1 /cut2 /cut3 /cut4	16.87368 18.82332 21.13949 23.86274	5.605875 5.652394 5.76247 5.943079			5.886367 7.744829 9.845257 12.21452	27.86099 29.90181 32.43372 35.51096

## Testing proportional odds assumption

. * testing pr	oportional o	dds assumptio	on			
. ologit rep77	'length mpg 1	lenxmpg				
Iteration 0: Iteration 1: Iteration 2: Iteration 3:	log likeliho log likeliho log likeliho log likeliho	bod = -89.89 bod = -83.93 bod = -83.80 bod = -83.80	5098 8395 4843 3935			
Ordered logistic regression Log likelihood = - <b>83.803935</b>				Numbe LR ch Prob Pseud	r of obs = i2(3) = > chi2 = o R2 =	66 12.18 0.0068 0.0678
rep77	Coef.	Std. Err.	z	P> z	[95% Conf	. Interval]
length mpg lenxmpg	.1106428 .8986173 0042101	.0421069 .3580163 .0020269	2.63 2.51 -2.08	0.009 0.012 0.038	.0281148 .1969182 0081828	.1931708 1.600316 0002374
/cut1 /cut2 /cut3 /cut4	20.29804 22.11432 24.15894 26.49523	8.159944 8.173392 8.25401 8.401218			4.304841 6.094763 7.981376 10.02915	36.29123 38.13387 40.3365 42.96132

#### Testing the interaction is a test of the proportional odds assumption.

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### **Corrected Ordinal Logistic Regression**

. ologit rep77	foreign leng	gth mpg rsea	t lenxmpg	l			
Iteration 0: Iteration 1: Iteration 2: Iteration 3: Iteration 4:	log likeliho log likeliho log likeliho log likeliho log likeliho	pod = -89.89 pod = -76.06 pod = -75.37 pod = -75.36 pod = -75.36	5098 8408 8436 5196 5182				
Ordered logist	ic regression	ı		Numbe	r of obs	= 6	6
				LR Cr	12( <b>5</b> )	= 29.0	0
log likelihood	75 36518	,		Prop		= 0.000	6
Log Thermood		L		FSEud	0 K2	- 0.101	.0
rep77	Coef.	Std. Err.	z	P> z	[95% Cor	nf. Interval	]
foreign length mpg rseat lenxmpg	3.089642 .1540429 .7136247 1923462 0027768	.8315193 .0456902 .3766148 .1074173 .0021298	3.72 3.37 1.89 -1.79 -1.30	0.000 0.001 0.058 0.073 0.192	1.459894 .0644918 0245267 4028807 0069511	4 4.7193 8 .24359 7 1.45177 2 .018187 1 .001397	9 4 6 9 6
/cut1 /cut2	25.48578 27.44362	8.885821 8.925229			8.06989 9.95049	5 42.9016 5 44.9367	57 15
/cut3 /cut4	32. 58999	9.207696			14. 54324	4 50.6367	5

## Ordered Probit models are an alternative

- Assumptions include constant proportionality across the cutpoints.
- An underlying normal distribution is assumed.
- The scale is such that one is dealing with standardized units.

## **Multinomial logistic regression**

#### for ordinal or categorical choice in the dependent variable

. mlogit insur	e age male no	onwhite site	2 site3			
Iteration 0: Iteration 1: Iteration 2: Iteration 3: Iteration 4:	log likeliho log likeliho log likeliho log likeliho log likeliho	bod = -555.8 bod = -534.7 bod = -534.3 bod = -534.3 bod = -534.3	5446 2983 6536 6165 6165			
Multinomial lo Log likelihooo	ogistic regres d = - <b>534.3616</b> 9	ssion 5		Numbe LR ch Prob Pseud	r of obs = i2(10) = > chi2 = lo R2 =	615 42.99 0.0000 0.0387
insure	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
Prepaid age male nonwhite site2 site3 _cons	011745 .5616934 .9747768 .1130359 5879879 .2697127	.0061946 .2027465 .2363213 .2101903 .2279351 .3284422	-1.90 2.77 4.12 0.54 -2.58 0.82	0.058 0.006 0.000 0.591 0.010 0.412	0238862 .1643175 .5115955 2989296 -1.034733 3740222	.0003962 .9590693 1.437958 .5250013 1412433 .9134476
Uninsure age male nonwhite site2 site3 _cons	0077961 .4518496 .2170589 -1.211563 2078123 -1.286943	.0114418 .3674867 .4256361 .4705127 .3662926 .5923219	-0.68 1.23 0.51 -2.57 -0.57 -2.17	0.496 0.219 0.610 0.010 0.570 0.030	0302217 268411 6171725 -2.133751 9257327 -2.447872	.0146294 1.17211 1.05129 2893747 .510108 1260135

(insure==Indemnity is the base outcome)

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