# Courses Seminars Tips Conference Apr/May/Jun Vol 30 No 2 The State Conference Apr/May/Jun Vol 30 No 2 Statistics Graphics Data Management & Analysis

# **Announcing Stata 14**

*Bayesian analysis* has come to Stata. Fit models using a Metropolis–Hastings algorithm, diagnose convergence, analyze posterior distributions, perform inference, and much, much more.

Unicode. Здравствуйте. こんにちは. Hello. Use Unicode for variable names, labels, data, and whatever else you wish.

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The Stata News

Executive Editor.....Karen Strope Production Supervisor .....Annette Fett



#### <sup>2</sup> In the spotlight: Bayesian "random-effects" models

Stata 14 introduced **bayesmh** for fitting Bayesian models. You can choose from one of many built-in models or write your own. See **stata.com/stata14/bayesian-analysis** and **stata.com/stata14/bayesian-evaluators** for details.

In this article, we show you how to use **bayesmh** to fit a Bayesian "random-effects" model. We write "random effects" in quotes because all effects (parameters) are considered random within the Bayesian framework. These models are typically referred to as Bayesian multilevel or Bayesian hierarchical models.

We revisit, using the Bayesian approach, the random-effects meta-analysis model described in example 6 of [ME] **me**. The term "meta-analysis" refers to a statistical analysis that involves summarizing results from similar but independent studies.

We consider data from Turner et al. (2000) that contain estimates of treatment effects expressed as log odds-ratios (**InOR**) and their respective variances (**var**) from nine clinical trials that examined the effect of taking diuretics during pregnancy on the risk of preeclampsia. Negative **InOR** values indicate that taking diuretics lowers the risk of preeclampsia. The model can be written as

$$\begin{aligned} \mathbf{y}_i &\sim \mathbf{N}(\boldsymbol{\mu}_i, \boldsymbol{\sigma}_i^{\ 2}) \\ \boldsymbol{\mu}_i &\sim \mathbf{N}(\boldsymbol{\theta}, \boldsymbol{\tau}^2) \end{aligned}$$

where  $\mu_i$  is the mean treatment effect of each trial,  $\theta$  is an overall mean,  $\sigma_i^2$  is the variance of the observed treatment effect and is considered fixed, and  $\tau^2$  is the between-trial variance.  $\theta$  and  $\tau^2$  are parameters of interest— $\tau^2$  close to 0 would suggest homogeneity across studies in log odds-ratio estimates.

In example 6 of [ME] **me**, we fit this random-effects model using **meglm** and obtain the estimates of  $\theta$  and  $\tau^2$  of -0.52 and 0.24 with their respective 95% confidence intervals of [-0.92, -0.11] and [0.048, 1.19].

For our Bayesian analysis, we need to additionally specify priors for  $\theta$  and  $\tau^2$  in model (1). Notice that the randomeffects model (1) already assumed a normal prior for each individual trial effect  $\mu_i$ . We consider fairly noninformative normal and inverse gamma prior distributions for the parameters  $\theta$  and  $\tau^2$ .

 $\theta \sim \text{Normal}(0, 10000)$  (2)  $\tau^2 \sim \text{IG}(0.0001, 0.0001)$ 

To fit model (1)–(2) using **bayesmh**, we type

```
. fvset base none trial
. bayesmh lnOR i.trial, noconstant likelihood(normal(var))
    prior({lnOR:i.trial}, normal({theta},{tau2}))
    prior({theta}, normal(0,10000))
    prior({tau2}, igamma(0.0001,0.0001))
    block({lnOR:i.trial}, split) block({theta}, gibbs)
    block({tau2}, gibbs) dots
```

The first four lines of the **bayesmh** specification are the straightforward model specification. The last two lines improve the efficiency of the sampler—a step that is crucial when fitting high-dimensional hierarchical models such as random-effects models. We sample all parameters separately by placing them in individual blocks and specifying option **split** for levels of **trial**, and we also request Gibbs sampling for  $\theta$  and  $\tau^2$ .

Because this is a random-effects example, we feel that a note of caution is in order. **bayesmh** uses an adaptive random-walk Metropolis–Hastings algorithm to fit all models (with potential Gibbs updates for some parameters). This algorithm provides an exceptionally flexible framework for fitting any Bayesian model. That flexibility comes with a price. The algorithm becomes inefficient for models with many parameters and may become prohibitively slow for some models. So, in theory, you can specify models with any number of levels of hierarchy and with any number of effects within a hierarchy. In practice, however, models with many random effects or many hierarchical levels may be infeasible. This poses no problem for our example with nine effects, but would likely be problematic for problems with thousands of random effects.

#### Here is the output:

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view bayes1.smcL X						
3					Dialog •	Also see - Jump
 Model summary					-	
lnOR ~ norm	al(xb_lnOR,va	ar)				
Prior.						
{lnOR:i.tri	al} ~ normal	({theta},{ta	au2})			(1)
Hyperpriors:						
{theta} ~ n	ormal(0,1000	D)				
{tau2} ~ i	gamma (0.0001,	,0.0001)				
(1) Parameter	s are element	ts of the li	inear form	xb_lnOR.		
				MCMC ite	rations =	12 500
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Bayesian norm Metropolis-Ha Log marginal	al regression stings and G likelihood =	-10.005871	ıg	Burn-in MCMC sam Number o Acceptan Efficien	= ple size = f obs = ce rate = cy: min = avg = max =	2,500 10,000 9 .5267 .05966 .1284 .2683
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Bayesian norm Metropolis-Ha Log marginal : 	al regression stings and G: likelihood = Mean	-10.005871 Std. Dev.	ng MCSE	Burn-in MCMC sam Number o Acceptan Efficien Median	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred.	2,500 10,000 9 .5267 .05966 .1284 .2683 .tailed Interval]
Bayesian norm Metropolis-Ha Log marginal : 	<pre>Al regression stings and G: likelihood =     Mean    1725911</pre>	-10.005871 Std. Dev. .3411875	ng MCSE .008538	Burn-in MCMC sam Number o Acceptan Efficien Median	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149	2,500 10,000 9 .5267 .05966 .1284 .2683 .2683 .tailed Interval]
Bayesian norm Metropolis-Ha Log marginal : 	<pre>Al regression stings and G: likelihood =</pre>	-10.005871 Std. Dev. .3411875 .3054875	MCSE .008538 .009207	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055	= ple size = f obs = ce rate = avg = max = Equal- [95% Cred. 830149 -1.406827	2,500 10,000 9 .5267 .05966 .1284 .2683 .tailed Interval] .52997 2325144
Bayesian norm Metropolis-Ha Log marginal : 	Mean 1725911 848563	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147	MCSE .008538 .009207 .010496	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789	2,500 10,000 9 .5267 .05966 .1284 .2683 .2683 .tailed Interval] .52997 2325144 2051206
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4	Mean 1725911 7802188 848563 9614017	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .4446485	MCSE .008538 .009207 .010496 .01509	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434	= ple size = f obs = ce rate = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545	2,500 10,000 9 .5267 .05966 .1284 .2683 - tailed Interval] 2325144 2051206 2247392
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4 5	<pre>Al regression stings and G: likelihood =</pre>	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .4446485 .3241574	MCSE .008538 .009207 .010496 .013271	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545 -1.749594	2,500 10,000 9 .5267 .05966 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .20597 2325144 2051206 .2247392 4724761
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4 5 6	1725911 7802188 848563 9614017 -1.090177 3107003	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .444685 .3241574 .0983935	MCSE .008538 .009207 .010496 .01509 .013271 .002373	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318 3104993	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545 -1.749594 5097513	2,500 10,000 9 .5267 .05966 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2051206 .2247392 .4724761 1120432
Bayesian norm Metropolis-Ha Log marginal 1 InOR trial 1 2 3 4 5 6 7	Mean 1725911 7802188 848563 9614017 -1.090177 3107003 3335097	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .4446485 .3241574 .0983935 .289512	MCSE .008538 .009207 .010496 .01509 .013271 .002373 .00702	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318 3104993 3430311	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545 749594 5097513 8841905	2,500 10,000 9 .5267 .05966 .1284 .2683 tailed Interval] .52997 2325144 2051206 2247392 4724761 1120432 .2680654
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4 5 6 7 8	<pre>Al regression stings and G: likelihood =</pre>	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .446485 .3241574 .0983935 .289512 .5472792	MCSE .008538 .009207 .010496 .01509 .013271 .002373 .00702 .018604	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318 3104993 3430311 086212	= ple size = f obs = ce rate = cy: min = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545 -1.749594 5097513 8841905 927254	2,500 10,000 9 .5267 .05966 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2683 .1284 .2051206 .2247392 .4724761 .1120432 .2680654 1.233408
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4 5 6 7 8 9	<pre>Al regression stings and G: likelihood =</pre>	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .4446485 .3241574 .0983935 .289512 .5472792 .2550613	MCSE .008538 .009207 .010496 .013271 .002373 .00702 .018604 .009728	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318 3104993 3430311 086212 0318037	= ple size = f obs = ce rate = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.895545 -1.749594 5097513 8841905 927254 5020652	2,500 10,000 9 .5267 .05966 .1284 .2683 -tailed Interval] 52997 2325144 2051206 2247392 4724761 1120432 .2680654 1.233408 .4952697
Bayesian norm Metropolis-Ha Log marginal : InOR trial 1 2 3 4 5 6 7 8 9 theta	1725911 1725911 7802188 848563 9614017 -1.090177 3107003 3335097 0148314 0232332 5065265	-10.005871 -10.005871 Std. Dev. .3411875 .3054875 .354147 .4446485 .3241574 .0983935 .289512 .5472792 .2550613 .2438874	MCSE .008538 .009207 .010496 .01509 .013271 .002373 .00702 .018604 .009728 .004708	Burn-in MCMC sam Number o Acceptan Efficien Median 1960632 7652055 8291194 9214434 -1.091318 3104993 3430311 086212 0318037 503503	= ple size = f obs = ce rate = avg = max = Equal- [95% Cred. 830149 -1.406827 -1.593789 -1.898545 -1.749594 5097513 8841905 927254 5020652 -1.008817	2,500 10,000 9 .5267 .05966 .1284 .2683 .2683 .tailed Interval] .52997 2325144 2051206 2247392 4724761 1120432 .2680654 1.233408 .4952697 0171035

Because we used noninformative priors, our Bayesian results are similar to the frequentist results from example 6. For example, the posterior mean estimate of the overall mean  $\theta$  is -0.51 with a 95% credible interval of [-1.01, -0.017] that represents the ranges to which  $\theta$  belongs with a probability of 0.95.

We use **bayesgraph** to evaluate MCMC convergence visually. For example, here are diagnostics for  $\theta$  and  $\tau^2$ :

. bayesgraph diagnostics {theta}, histopts(normal)



#### . bayesgraph diagnostics {tau2}



4

Our visual diagnostics raise no concern for these parameters. We can also check MCMC convergence for trial-specific  $\mu_i$ 's by typing

# . bayesgraph diagnostics {lnOR:i.trial} (output omitted)

We can test whether taking diuretics reduces the risk of preeclampsia overall by computing the probability that  $\theta$  is negative.

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view bayes2.smcl 🗙	-
D.	Dialog * Also see * Jump to *
. bayestest ir	terval {theta}, upper(0) ^
Interval tests	MCMC sample size = 10,000
prob1 :	{theta} < 0
	Mean Std. Dev. MCSE
prob1	.9779 0.14702 .0019344
	CAP NUM OVR 🦼

That probability is 0.98.

If desired, we can also compute an estimate of the overall odds ratio.

•		Viewer -	view bayes	3.smcl		- 0	×	
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D.					Dialog 🐐 Als	o see - Ju	imp to	- v
. bayesstats s	ummary (OR:	exp({theta}	))					^
Posterior summ	ary statisti exp({theta]	ics		MCMC sa	mple size =	10,0	000	
	Mean	Std. Dev.	MCSE	Median	Equal-t [95% Cred.	tailed Interva	1]	
OR	.6209171	.1589714	.002954	.6044097	.3646501	.9830	42	
					C.	AP NUM	OVR	<b>•</b>

A neat feature of our Bayesian analysis is that we can explore the distributions of the estimated parameters. For example, we can look at distributions of effects from individual trials.

```
. bayesgraph histogram {lnOR:i.trial},
  byparm(legend(off) noxrescale noyrescale
  title(Posterior distributions of trial effects))
  normal xline(-0.51)
```



The posterior distributions are fairly normal for most trials. Posteriors for some trials are more closely centered on the overall mean of -0.51, particularly for trials 2 and 7.

There is a noticeable variability in the estimated treatment effects between trials. Trials 6 and 9 are more precise compared with other trials.

We can also test for an effect in each trial. We can estimate a probability that an effect is negative (meaning diuretics work) for each trial. For example,

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D.				Dialog + Also	see - Jump to -
. bayestest in	nterval ({lnO	R:2.trial},	upper(0))	({lnOR:9.trial},	upper(0)) ^
Interval test:	s MCMC sa	mple size =	10,000		
probl prob2	: {lnOR:2.tri : {lnOR:9.tri	al} < 0 al} < 0			
	Mean	Std. Dev.	MCSE		
probl	.9989	0.03315	.0005907		
prob2	.5458	0.49792	.0153296		
				CAF	NUM OVR

The probability of a negative treatment effect is almost 1 for trial 2 and only about 0.55 for trial 9.

#### Reference

Turner, R. M., R. Z. Omar, M.Yang, H. Goldstein, and S. G. Thompson. 2000. A multilevel model framework for meta-analysis of clinical trials with binary outcomes. *Statistics in Medicine* 19: 3417–3432.

#### - Yulia Marchenko Director of Biostatistics, StataCorp

— Nikolay Balov

Senior Statistician and Software Developer, StataCorp

## **2015 International Stata Users Group meetings**

#### Germany



Nuremberg stata.com/meeting/germany15

June 26, 2015

#### Japan



Tokyo stata.com/meeting/japan15

August 28, 2015

#### Sweden



Stockholm September 4, 2015 stata.com/meeting/nordic-and-baltic15

#### UK



London stata.com/meeting/uk15

September 10-11, 2015

Portugal



Lisbon stata.com/meeting/portugal15

#### **Australia**



Canberra Septemberstata.com/meeting/australia15

September 24–25, 2015

September 18, 2015

#### Italy



Florence stata.com/meeting/italy15

November 12–13, 2015

Keep up with future Stata Users Group meetings. We post our schedule at **stata.com/meeting**. Want to be notified when new meeting information is posted? Go to **stata.com/alerts** and sign up for an email alert today.

#### 6 In the spotlight: Formatting Excel<sup>®</sup> tables from within Stata

New capabilities of **putexcel** in Stata 14 let you format cells and fonts in Excel. This means that you can now easily export matrices, expressions, and stored results from Stata to Excel and control how they appear. You can also insert Stata graphs and add cell formulas. Now it's easy to format the cells to create custom tables or reports. Let's see how it's done.

Suppose I am estimating a fractional-response model for 401(k) participation and want to create a table of my results that I could include in a presentation or publication. A short description of the variables is shown to the right.

. webuse 401k
. fracreg probit prate mrate sole
(output omitted)

After I fit my model, I want to write out the estimated coefficients and standard errors to Excel. Most estimation commands in Stata store results in the **r(table)** matrix, giving you an easy way to access estimated coefficients, standard errors, test statistics, and the like from a single stored

Variable	Description
prate	participation rate
mrate	plan match rate, per \$
sole	=1 if only retirement plan

result. All you need to do is extract the appropriate rows and columns from the matrix.

I do this by typing

```
. matrix a = r(table)
```

```
. matrix b = a[1 ..2,1 ...]'
```

. putexcel C3=matrix(b) using 401k\_report.xlsx replace

	Α	В	С	D	Е	F 🔺
1						
2						
3			0.676082	0.038644		
4			0.214518	0.026416		
5			0.653441	0.019444		
6						
7						-
	<	Sheet1	$\oplus$	: 4		Þ
REA	ΔY	E		-	-	+ 100%

But my table is not quite publication-ready yet.

I can add bold column titles, "Estimate" and "S.E.", and a cell border between the title and results to the worksheet by typing

To add row labels and a cell border between the label and results, I type

Now, I want to center the column text and results and format the numeric output to two decimals:

I now have a nice-looking table.

	А	В	С	D	E	
1						
2			Estimate	S.E.		
3		Matching Rate	0.68	0.04		
4		Only Option	0.21	0.03		
5		Constant	0.65	0.02		
6						
7						-
	<	Sheet1	$\oplus$	4		Þ
REA	ωDY		•	-	+	100%

But, **putexcel** can do even more. You can also write a wide range of graph file formats, including PNG, JPEG, WMF, and TIFF.

For example, I can add a bar graph of the average participation rate for companies over whether the 401(k) is the only retirement option offered by typing

- . graph bar (mean) prate, over(sole) ytitle("Participation Rate") title("Plan Participation by Number of Options")
- . graph export bar1.png
- . putexcel (C7)=picture("bar1.png") using 401k\_report.xlsx, modify

My worksheet now looks like this:



There are many more formats and settings that you can change in Excel by using **putexcel**. To view a list, see [P] **putexcel**.

- Kevin Crow Senior Software Developer, StataCorp

# STATA CONFERENCE COLUMBUS

Come join us in Columbus, home to the state capital of Ohio and Ohio State University, for two days of networking and Stata exploration. The conference includes, in addition to user contributions, presentations by StataCorp developers on new Stata 14 features.

Don't miss this opportunity to connect with fellow researchers as well as developers who wrote Stata 14!

## **Preliminary program**

# Estimating treatment effects for ordered outcomes using maximum simulated likelihood

Christian Gregory Economic Research Service, USDA

# Linear dynamic panel-data estimation using maximum likelihood and structural equation modeling

Richard Williams Department of Sociology, University of Notre Dame

Paul Allison Department of Sociology, University of Pennsylvania

Enrique Moral Benito Banco de España Madrid

#### 15 years a consultant

Phil Ender UCLA Statistical Consulting Group (Ret)

#### Robust inference in regression-discontinuity designs

Matias Cattaneo University of Michigan

Sebastian Calonico University of Michigan

Rocio Titiunik University of Michigan

# Estimation in panel data with individual effects and AR(p) remainder disturbances

Long Liu Department of Economics, The University of Texas at San Antonio

#### Item response theory models in Stata Rebecca Pope Health Econometrician, StataCorp

When	July 30–31, 2015
Where	Hyatt Regency Columbus
	350 North High Street Columbus, Ohio
Who	Stata developers

- You and Stata users from around the world
- **Cost** \$195 two days, \$75 student \$125 one day, \$50 student Optional dinner TBA

#### Meta-analysis on the effects of interviewer supportiveness on the accuracy of children's reports

Christine Wells Statistical Consulting Group, UCLA Karen Saywitz, PhD

UCLA

Rakel Larson, MA University of California, Riverside

Sue Hobbs, PhD University of California, Davis

# tetrad: A program for confirmatory tetrad analysis

Shawn Bauldry University of Alabama at Birmingham

Kenneth Bollen University of North Carolina at Chapel Hill

# Postestimation parameter recentering and rescaling

Douglas Hemken Social Science Computing Cooperative, University of Wisconsin–Madison

#### Statistical process control charts

Barbara Williams Virginia Mason Medical Center

#### Data workflows with Stata and Python Stephen Childs

Education Policy Research Initiative, University of Ottawa

Dejan Pavlic Education Policy Research Initiative

# Distribution-free estimation of heteroskedastic binary-response models in Stata

Jason Blevins Department of Economics, The Ohio State University

Shakeeb Khan Duke University

# A comparison of modeling scales in flexible parametric models

Noori Akhtar-Danesh McMaster University

# Estimating Markov-switching regression models in Stata

Ashish Rajbhandari Senior Econometrician, StataCorp

#### midasinla: midas goes Bayesian via R-INLA

Ben Adarkwa Dwamena University of Michigan Medical School

## Between and beyond: Irregular series,

interpolation, variograms, and smoothing Nicholas Cox

Department of Geography, Durham University

#### Public program sensitivity: Using ROC curves to characterize classification efficiency of state Medicaid systems

Lisa Frazier

John Glenn College of Public Affairs, The Ohio State University

#### Small-sample inference for linear mixedeffects models

Xiao Yang Senior Statistician and Software Developer, StataCorp

#### Development of a project-based statistics course for applied biostatistics using Stata

Frank Snyder Purdue University

#### Brewing color schemes in Stata: Making it easier for end users to customize Stata graphs William Buchanan

Mississippi Department of Education

# Colombian industrial structure behavior and its regions between 1974 and 2005

Luis Fernando López Pineda Chamber of Commerce of Cartagena

# Accommodations

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Hyatt Regency Columbus 350 North High Street Columbus, Ohio 43215 (614) 463-1234 **resweb.passkey.com/go/statacorp15** 

See you in Columbus!

# Scientific committee

- Stanley Lemeshow (chair of review team) The Ohio State University Biostatistics
- Timothy R. Sahr (coordinator) The Ohio Colleges of Medicine Government Resource Center Applied Research
- Marcus Berzofsky RTI, International Survey Research
- Christopher Browning The Ohio State University Sociology
- Anand Desai The Ohio State University Public Policy
- Christopher Holloman The Ohio State University Statistics
- Bo Lu The Ohio State University Biostatistics
- Eric Seiber The Ohio State University Health Economics



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## • Working efficiently with Stata

Instructor: Demetris Christodoulou, MEAFA General Convenor June 29, 2015

- Introduction to programming Instructor: Demetris Christodoulou, MEAFA General Convenor June 30, 2015
- Treatment effects Instructor: David Drukker, Director of Econometrics StataCorp LP

July 1-2, 2015

• **Programming estimation commands** Instructor: David Drukker, Director of Econometrics StataCorp LP July 3, 2015

You can attend any single day or combination of days. Spaces are limited. For more information, visit **stata.com/news/meafa2015**.

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## 12 Testing for endogeneity: New feature for eteffects in Stata 14

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If an unobserved variable affects treatment and outcome, we have an endogeneity problem and cannot obtain accurate estimates of effects using conventional treatment-effects estimators.

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How?

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#### . estat endogenous

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