

Running MLwiN from within Stata: the `runmlwin` command

Research Methods Festival
Oxford
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What is `runmlwin`?

- `runmlwin` is a Stata command to run MLwiN seamlessly from within Stata
 - MLwiN offers fast estimation of a wide range of multilevel models, but has limited data management, graphics and programming facilities
 - Stata offers a limited range of multilevel models, but has excellent facilities for pre- and post-estimation data management and graphics and many model testing and interpretation routines
 - `runmlwin` capitalises on the best features of both packages
- But what if you use R rather than Stata...
 - Zheng Zheng Zhang is developing `r2mlwin` to run MLwiN from within R
 - `r2mlwin` will provide the same functionality as `runmlwin`

Multilevel modelling in Stata

- Stata provide the `xtmixed`, `xtmelogit` and `xtmepoisson` commands
 - Limited range of models can be specified
 - Computationally quite slow
- Sophia Rabe-Hesketh and colleagues have developed the `gllamm` command
 - Wide range of models can be specified
 - Computationally slow
- Other user-written multilevel modelling commands include: `hlm`, `realcomimpute`, `runmplus`, `sabrestata`, `winbugs`

Multilevel modelling in MLwiN

1. Estimation of multilevel models for continuous, binary, **ordered categorical**, **unordered categorical** and count data
2. Fast estimation via classical and **Bayesian** methods
3. Estimation of multilevel models for cross-classified and **multiple membership** non-hierarchical data structures
4. Estimation of **multilevel multivariate response models**, **multilevel spatial models**, **multilevel measurement error models**, **multilevel multiple imputation models** and **multilevel factor models**
5. Free to UK academics, thanks to ESRC funding

1. CONTINUOUS RESPONSE MODELS

Two-level variance components model

- Inner-London schools exam scores data set
- Main MLwiN User Manual example (the “tutorial” data set)
- 4059 students nested within 65 schools

$$\mathbf{normexam}_{ij} = \beta_0 + u_j + e_{ij}$$

$$u_j \sim N(0, \sigma_u^2)$$

$$e_{ij} \sim N(0, \sigma_e^2)$$



Statistics/Data Analysis
MP - Parallel Edition

12.1 Copyright 1985-2011 StataCorp LP
 StataCorp
 4905 Lakeway Drive
 College Station, Texas 77845 USA
 800-STATA-PC <http://www.stata.com>
 979-696-4600 stata@stata.com
 979-696-4601 (fax)

2-user 2-core stata network perpetual license:
 Serial number: 50120527735
 Licensed to: ZoneA
 University of Bristol

Notes:
 1. (/v# option or -set maxvar-) 5000 maximum variables

running C:\Program Files (x86)\Stata12\sysprofile.do ...

running C:\Users\gl9158\profile.do ...

.

Variables

Variable	Label
----------	-------

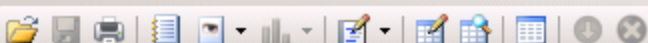
There are no items to show.

Properties

Variables	
Name	
Label	
Type	
Format	
Value Label	
Notes	

Data	
------	--

Command



STATA (R)
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.

Variables ↑ ↓ ×

Variable	Label
----------	-------

There are no items to show.

Properties ↑ ↓ ×

🔒 | ← →

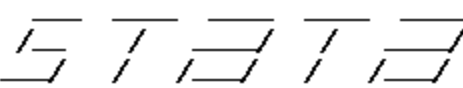
📁 Variables

Name	
Label	
Type	
Format	
Value Label	
Notes	

Command

use <http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial.dta>



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. use <http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial.dta>

.

Variable	Label
school	School ID
student	Student ID
normexam	Age 16 exam score...
cons	Constant
standlrt	Age 11 exam score...
girl	Girl
schgend	School gender
avslrt	School average LR...
schav	School average LR...
vrband	Age 11 verbal reas...

Variables	
Name	school
Label	School ID
Type	byte
Format	%9.0g
Value Label	
Notes	

Command

The `runmlwin` command syntax

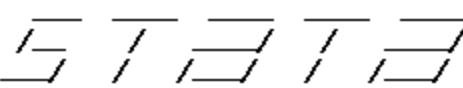
$$\mathbf{normexam}_{ij} = \beta_0 + u_j + e_{ij}$$

$$u_j \sim N(0, \sigma_u^2)$$

$$e_{ij} \sim N(0, \sigma_e^2)$$

```
. runmlwin normexam cons, ///  
    level2(school: cons) ///  
    level1(student: cons)
```



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.

Variable	Label
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vrband	Age 11 verbal reas...

Variables	
Name	school
Label	School ID
Type	byte
Format	%9.0g
Value Label	
Notes	

Command

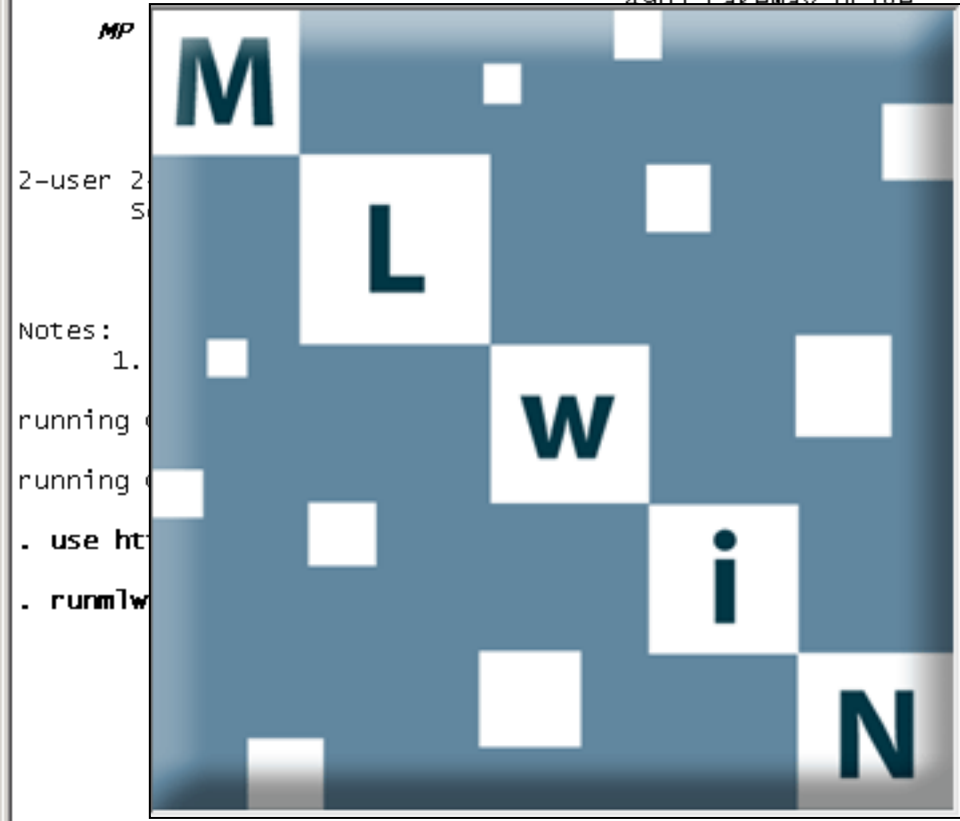
runmlwin normexam cons, level2[school: cons] level1[student: cons]



STATA (R)
 Statistics/Data Analysis

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 StataCorp
 4905 Lakeway Drive

Variable	Label
school	School ID
student	Student ID



MLwiN
 Version 2.25

© Centre for Multilevel Modelling
 University of Bristol

Software authors :
 Jon Rasbash
 and
 William Browne
 Michael Healy
 Bruce Cameron
 Christopher Charlton

February 2012

We are grateful to the ESRC for their sustained support.

m score...
 m score...
 der
 age LR...
 age LR...
 bal reas...

Command

Name	Label	Type	Format	Value Label	Notes
school	School ID	byte	%9.0g		

MLwiN - [Equations]

File Edit Options Model Estimation Data Manipulation Basic Statistics Graphs Window Help

Start More Stop IGLS Estimation control.. Resume macro Abort Macro

$$\text{normexam}_{ij} \sim N(XB, \Omega)$$

$$\text{normexam}_{ij} = \beta_{0ij} \text{cons}$$

$$\beta_{0ij} = \beta_0 + u_{0j} + e_{0ij}$$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim N(0, \Omega_u) : \Omega_u = \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} e_{0ij} \end{bmatrix} \sim N(0, \Omega_e) : \Omega_e = \begin{bmatrix} \sigma_e^2 & 0 \\ 0 & 0 \end{bmatrix}$$

(4059 of 4059 cases in use)

Name + - Add Term Estimates Nonlinear Clear Notation Responses Store Help Zoom 150

random fixed iteration 0 Equations

$$\text{normexam}_{ij} \sim N(XB, \Omega)$$

$$\text{normexam}_{ij} = \beta_{0ij} \text{cons}$$

$$\beta_{0ij} = -0.013(0.054) + u_{0j} + e_{0ij}$$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim N(0, \Omega_u) : \Omega_u = \begin{bmatrix} 0.169(0.032) \end{bmatrix}$$

$$\begin{bmatrix} e_{0ij} \end{bmatrix} \sim N(0, \Omega_e) : \Omega_e = \begin{bmatrix} 0.848(0.019) \end{bmatrix}$$

$$-2 * \log \text{likelihood}(\text{IGLS Deviance}) = 11010.648(4059 \text{ of } 4059 \text{ cases in use})$$

File Edit Data Graphics Statistics User Window Help



```
. use http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial.dta
. runmlwin normexam cons, level2(school: cons) level1(student: cons)
```

```
MLWIN 2.25 multilevel model           Number of obs   =      4059
Normal response model
Estimation algorithm: IGLS
```

Level variable	No. of Groups	observations per Group		
		Minimum	Average	Maximum
school	65	2	62.4	198

```
Run time (seconds) =      17.13
Number of iterations =        3
Log likelihood      = -5505.3242
Deviance           =  11010.648
```

normexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.0131668	.0536254	-0.25	0.806	-.1182706	.091937

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school					
	var(cons)	.1686251	.0324466	.1050309	.2322194
Level 1: student					
	var(cons)	.8477613	.0189712	.8105786	.8849441

Command

Variable	Label
school	School ID
student	Student ID
normexam	Age 16 exam score...
cons	Constant
standlrt	Age 11 exam score...
girl	Girl
schgend	School gender
avslrt	School average LR...
schav	School average LR...
vrband	Age 11 verbal reas...

Properties	
Variables	
Name	school
Label	School ID
Type	byte
Format	%9.0g
Value Label	
Notes	



```
. runmlwin normexam cons, level2(school: cons) level1(student: cons)
```

```
MLwin 2.25 multilevel model          Number of obs      =      4059
Normal response model
Estimation algorithm: IGLS
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Level Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
school	65	2	62.4	198

```
Run time (seconds) =      17.13
Number of iterations =      3
Log likelihood      = -5505.3242
Deviance           = 11010.648
```

normexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.0131668	.0536254	-0.25	0.806	-.1182706	.091937

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school					
	var(cons)	.1686251	.0324466	.1050309	.2322194
Level 1: student					
	var(cons)	.8477613	.0189712	.8105786	.8849441

Add covariates

$$\text{normexam}_{ij} = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_j + e_{ij}$$

$$u_j \sim N(0, \sigma_u^2)$$

$$e_{ij} \sim N(0, \sigma_e^2)$$

```
. runmlwin normexam cons standlrt girl, ///  
  level2(school: cons) ///  
  level1(student: cons)
```

Include a random slope

$$\text{normexam}_{ij} = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij} + e_{ij}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

$$e_{ij} \sim N(0, \sigma_e^2)$$

```
. runmlwin normexam cons standlrt girl, ///  
  level2(school: cons standlrt) ///  
  level1(student: cons)
```

Allow for level 1 heteroskedasticity

$$\text{normexam}_{ij} = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij} \\ + e_{2ij} \text{girl}_{ij} + e_{3ij} \text{boy}_{ij}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

$$\begin{pmatrix} e_{2ij} \\ e_{3ij} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{e2}^2 & \\ 0 & \sigma_{e3}^2 \end{pmatrix} \right\}$$

- . generate boy = 1 - girl
- . runmlwin normexam cons standlrt girl, ///
level2(school: cons standlrt) ///
level1(student: girl boy, diagonal)

Retrieve the level 2 residuals

$$\begin{aligned} \text{normexam}_{ij} = & \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij} \\ & + e_{2ij} \text{girl}_{ij} + e_{3ij} \text{boy}_{ij} \end{aligned}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

$$\begin{pmatrix} e_{2ij} \\ e_{3ij} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{e2}^2 & \\ 0 & \sigma_{e3}^2 \end{pmatrix} \right\}$$

```
. runmlwin normexam cons standlrt girl, ///  
  level2(school: cons standlrt, residuals(u)) ///  
  level1(student: girl boy, diagonal)
```

Do not pause in MLwiN and do not display the group table in Stata

$$\begin{aligned} \mathbf{normexam}_{ij} = & \beta_0 + \beta_1 \mathbf{standlrt}_{ij} + \beta_2 \mathbf{girl}_{ij} + u_{0j} + u_{1j} \mathbf{standlrt}_{ij} \\ & + e_{2ij} \mathbf{girl}_{ij} + e_{3ij} \mathbf{boy}_{ij} \end{aligned}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

$$\begin{pmatrix} e_{2ij} \\ e_{3ij} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{e2}^2 & \\ 0 & \sigma_{e3}^2 \end{pmatrix} \right\}$$

```
. runmlwin normexam cons standlrt girl, ///  
    level2(school: cons standlrt, residuals(u)) ///  
    level1(student: girl boy, diagonal) nogroup nopause
```



```

. runmlwin normexam cons standlrt girl, ///
>     level2(school: cons standlrt, residuals(u)) ///
>     level1(student: girl boy, diagonal) ///
>     nogroup nopause

```

```

MLwin 2.25 multilevel model           Number of obs       =       4059
Normal response model
Estimation algorithm: IGLS
Run time (seconds) =           1.84
Number of iterations =           4
Log likelihood =       -4640.71
Deviance =           9281.4199

```

normexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.111534	.0433072	-2.58	0.010	-.1964145	-.0266536
standlrt	.5529361	.0200758	27.54	0.000	.5135882	.5922841
girl	.1752785	.0324156	5.41	0.000	.1117451	.238812

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school				
var(cons)	.0862511	.017175	.0525887	.1199135
cov(cons,standlrt)	.0190537	.0066789	.0059632	.0321441
var(standlrt)	.0148919	.0044702	.0061304	.0236534
Level 1: student				
var(girl)	.5251641	.0152836	.4952088	.5551194
var(boy)	.5874345	.0209983	.5462786	.6285904



```

.
. runmlwin normexam cons standlrt girl, ///
>   level2(school: cons standlrt, residuals(u)) ///
>   level1(student: girl boy, diagonal) ///
>   nogroup nopause

```

```

MLwin 2.25 multilevel model           Number of obs       =       4059
Normal response model
Estimation algorithm: IGLS
Run time (seconds) =           1.84
Number of iterations =           4
Log likelihood =       -4640.71
Deviance =           9281.4199

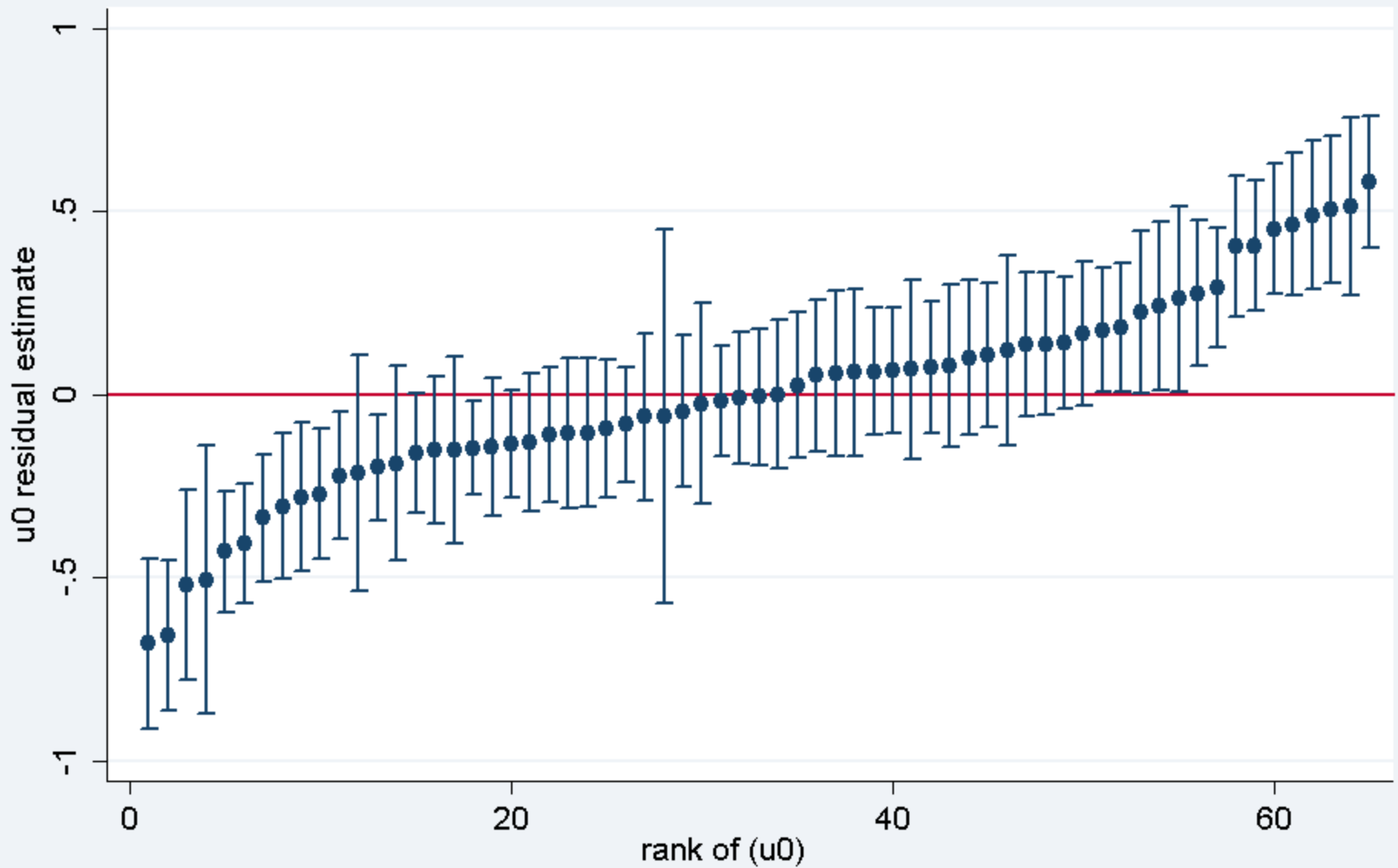
```

normexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.111534	.0433072	-2.58	0.010	-.1964145	-.0266536
standlrt	.5529361	.0200758	27.54	0.000	.5135882	.5922841
girl	.1752785	.0324156	5.41	0.000	.1117451	.238812

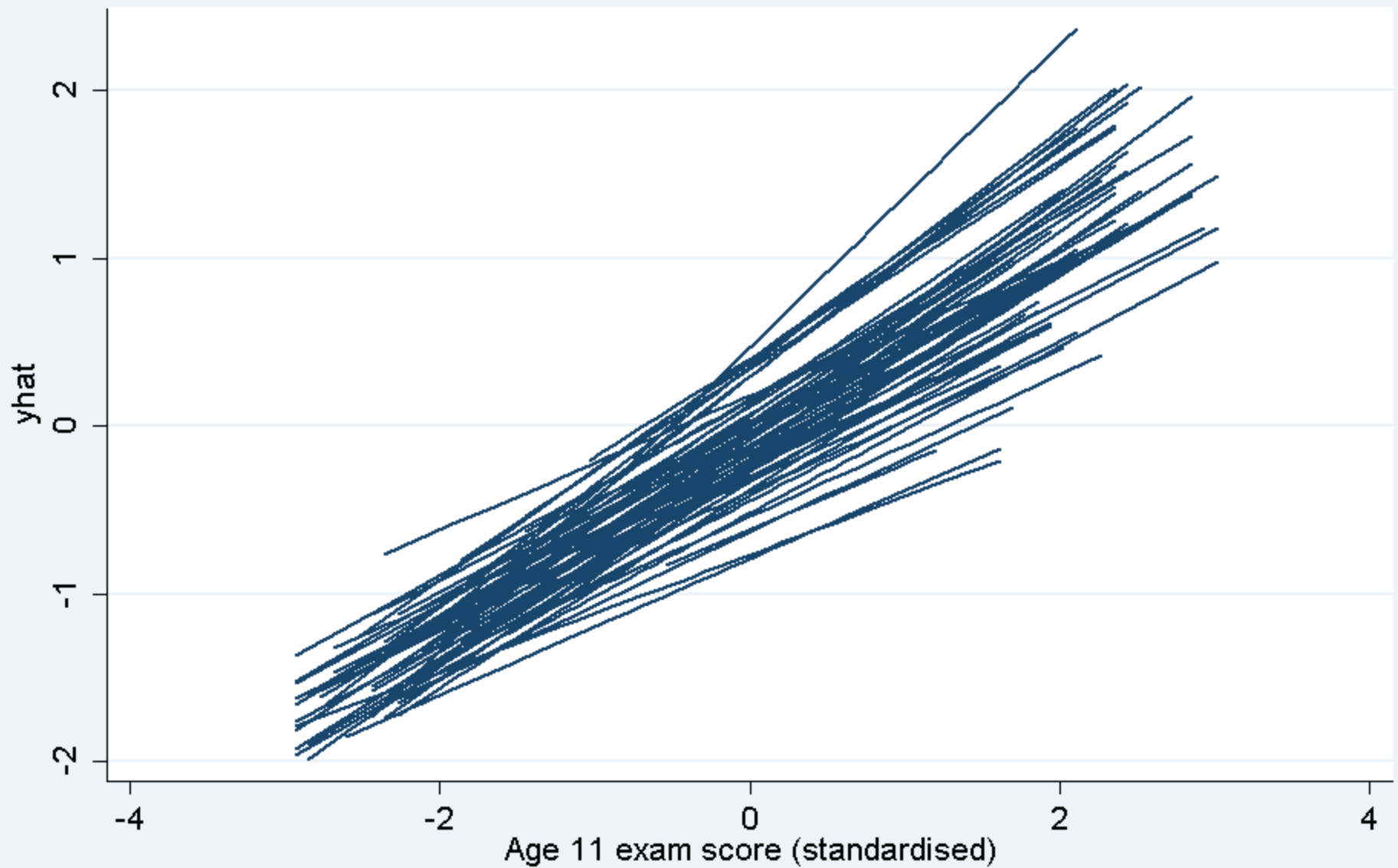
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school				
var(cons)	.0862511	.017175	.0525887	.1199135
cov(cons,standlrt)	.0190537	.0066789	.0059632	.0321441
var(standlrt)	.0148919	.0044702	.0061304	.0236534
Level 1: student				
var(girl)	.5251641	.0152836	.4952088	.5551194
var(boy)	.5874345	.0209983	.5462786	.6285904

Variables

Variable
school
student
normexam
cons
standlrt
girl
schgend
avslrt
schav
vrband
boy
u0
u1
u0se
u1se



```
. bysort school: keep if _n==1  
. egen u0rank = rank(u0)  
. serrbar u0 u0se u0rank, scale(1.96) yline(0)
```

```
. gen yhat = [FP1]cons + [FP1]stand*stand + u0 + u1*stand  
. sort school standlrt  
. line yhat standlrt, connect(ascending)
```



```
. lrtest model1 model2
```

```
Likelihood-ratio test                    LR chi2(5) = 1729.23
(Assumption: model1 nested in model2)    Prob > chi2 = 0.0000
```

```
.
.
.
.
.
.
```

```
. test [RP1]var(girl) = [RP1]var(boy)
```

```
( 1) [RP1]var(girl) - [RP1]var(boy) = 0
```

```
      chi2( 1) = 5.74
      Prob > chi2 = 0.0166
```

```
.
.
.
.
.
```

```
. nlcom (Boy_VPC_xis0: [RP2]var(cons)/([RP2]var(cons) + [RP1]var(boy)))
```

```
Boy_VPC_xis0: [RP2]var(cons)/([RP2]var(cons) + [RP1]var(boy))
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Boy_VPC_xis0	.1280287	.0226244	5.66	0.000	.0836856	.1723718

2. BINARY RESPONSE MODELS

Random slope logistic model

$$\text{passexam}_{ij} \sim \text{Binomial}(1, \pi_{ij})$$

$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

- `. generate passexam = (normexam>0)`
- `. runmlwin passexam cons standlrt girl, ///`
 - `level2(school: cons standlrt) ///`
 - `level1(student:) ///`
 - `discrete(dist(binomial) link(logit) denom(cons)) ///`
 - `nogroup nopause`



```

. generate passexam = (normexam>0)

. runmlwin passexam cons standlrt girl, ///
> level2(school: cons standlrt) ///
> level1(student:) ///
> discrete(distribution(binomial) link(logit) denominator(cons)) ///
> nogroup nopause

```

```

MLwin 2.25 multilevel model           Number of obs       =       4059
Binomial logit response model
Estimation algorithm: IGLS, MQL1
Run time (seconds) =           1.61
Number of iterations =           6

```

passexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.0479964	.101761	-0.47	0.637	-.2474444	.1514515
standlrt	1.232918	.0581067	21.22	0.000	1.119031	1.346805
girl	.186636	.0956229	1.95	0.051	-.0007814	.3740534

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school				
var(cons)	.3701358	.0822183	.208991	.5312807
cov(cons,standlrt)	-.0444551	.0394446	-.0328549	.121765
var(standlrt)	.06152	.0364277	-.009877	.1329169

```

.
.

```

Fit model by PQL2 using MQL1 estimates as starting values

$$\text{passexam}_{ij} \sim \text{Binomial}(1, \pi_{ij})$$

$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ & \sigma_{u1}^2 \end{pmatrix} \right\}$$

```
. runmlwin passexam cons standlrt girl, ///  
  level2(school: cons standlrt) ///  
  level1(student:) ///  
  discrete(d(binomial) l(logit) de(cons) pql2) ///  
  initsprevious nopause
```

```

. runmlwin passexam cons standlrt girl, ///
> level2(school: cons standlrt) ///
> level1(student:) ///
> discrete(dist(binomial) link(logit) denom(cons) pq12) ///
> initsprevious nogroup nopause

```

Model fitted using initial values specified as parameter estimates from previous model

```

MLwin 2.25 multilevel model           Number of obs       =       4059
Binomial logit response model
Estimation algorithm: IGLS, PQL2
Run time (seconds) =           2.04
Number of iterations =           8

```

passexam	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
cons	-.0367105	.1120693	-0.33	0.743	-.2563622	.1829413
standlrt	1.358886	.0642726	21.14	0.000	1.232914	1.484858
girl	.2012481	.1013948	1.98	0.047	.0025179	.3999782

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school				
var(cons)	.4740776	.1031501	.2719071	.676248
cov(cons,standlrt)	.0625434	.0491646	-.0338175	.1589043
var(standlrt)	.0764959	.0443148	-.0103596	.1633514

.
.



```

. estimates table mql1 pq12, ///
> stats(11 N) b(%4.3f) stfmt(%4.0f) varwidth(18) newpanel

```

Variable	mql1	pq12
FP1		
cons	-0.048	-0.037
standlrt	1.233	1.359
girl	0.187	0.201

RP2		
var(cons)	0.370	0.474
cov(cons\standlrt)	0.044	0.063
var(standlrt)	0.062	0.076

RP1		
var(bcons_1)	1.000	1.000

Statistics	mql1	pq12
11		
N	4059	4059

```

.
.
.
.
.
.

```


3. SIMULATION STUDIES ARE NOW EASY



rodriguez and goldman (1995).do



```
1  * REPLICATE RODRIGUEZ AND GOLDMAN (1995)
2  clear
3  set seed 12345
4  postutil clear
5  postfile MQL1 ix fx cx sigmaf sigmac using "MQL1.dta", replace
6  set obs 2
7  generate cx = _n - 1
8  expand 10
9  sort cx
10 generate cid = _n
11 expand 2
12 bysort cid: gen fx = _n - 1
13 expand 10
14 bysort cid (fx): generate fid = _n
15 expand 2
16 bysort cid fid: gen ix = _n - 1
17 expand 10
18 bysort cid fid (ix): gen iid = _n
19 generate cons = 1
20 forvalues iteration = 1/100 {
21     display _n(5) as txt "Iteration " as res "`iteration'" as txt " of " as res "100"
22     generate c = rnormal(0,1)
23     bysort cid (fid iid): replace c = c[1]
24     generate f = rnormal(0,1)
25     bysort cid fid (iid): replace f = f[1]
26     generate y = rbinomial(1,invlogit(0*cons + 1*ix + 1*fx + 1*cx + f + c))
27     runmlwin y cons ix fx cx, level3(cid: cons) level2(fid: cons) level1(iid:) ///
28         discrete(distribution(binomial) link(logit) denominator(cons)) ///
29         nopause
30     post MQL1 ([FP1]ix) ([FP1]fx) ([FP1]cx) (sqrt([RP2]var(cons))) (sqrt([RP3]var(cons)))
31     drop c f y
32 }
33 postclose MQL1
34 use "MQL1.dta", clear
35 tabstat ix fx cx sigmaf sigmac, format(%3.2f)
36
```

4. MCMC ESTIMATION

Random slope logistic model

$$\text{passexam}_{ij} \sim \text{Binomial}(1, \pi_{ij})$$

$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_1 \text{standlrt}_{ij} + \beta_2 \text{girl}_{ij} + u_{0j} + u_{1j} \text{standlrt}_{ij}$$

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim \text{N} \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}$$

```
. runmlwin passexam cons standlrt girl, ///  
  level2(school: cons standlrt) ///  
  level1(student:) ///  
  discrete(d(binomial) 1(logit) de(cons)) ///  
  mcmc(burnin(500) chain(5000)) ///  
  initsprevious nogroup nopause
```



```

. runmlwin passexam cons standlrt girl, ///
> level2(school: cons standlrt) level1(student:) ///
> discrete(d(binomial) l(logit) de(cons)) ///
> mcmc(burnin(500) chain(5000)) initsprevious nogroup nopause

```

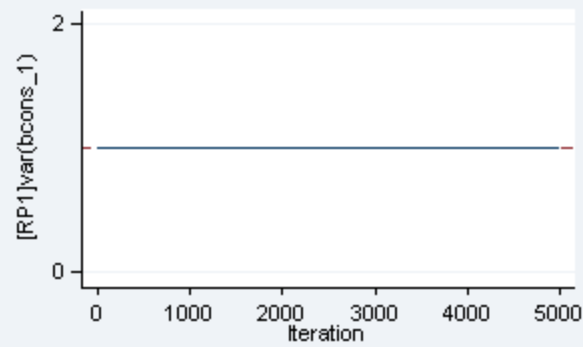
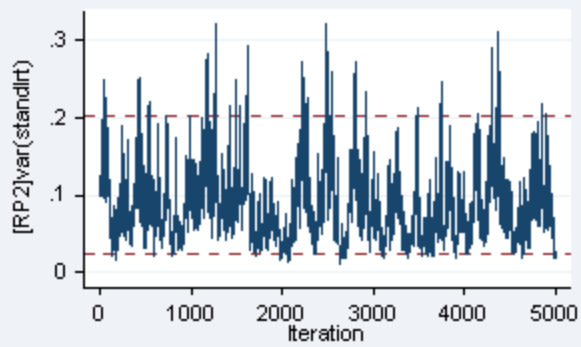
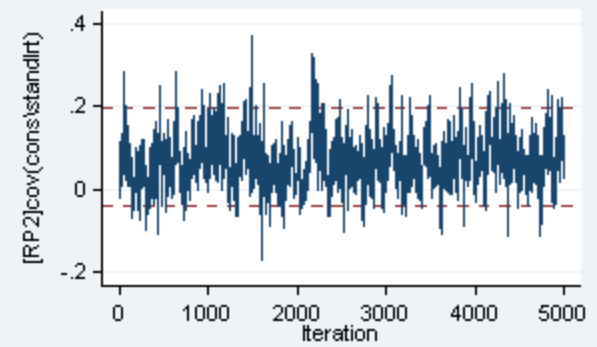
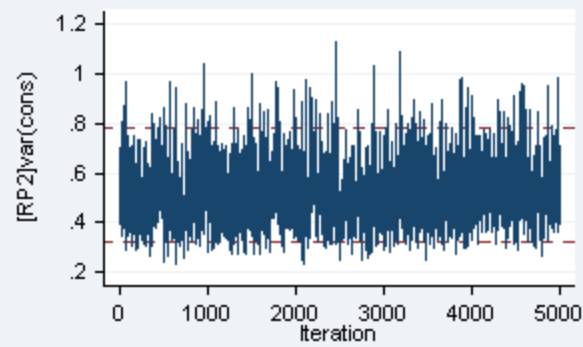
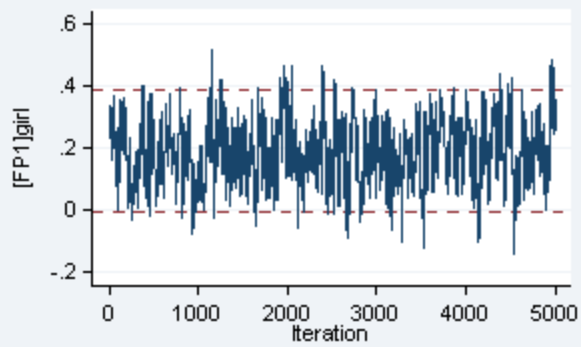
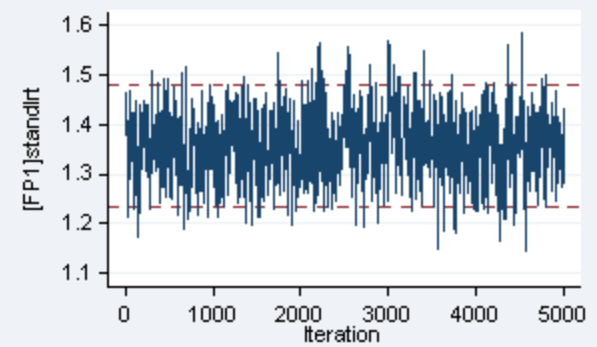
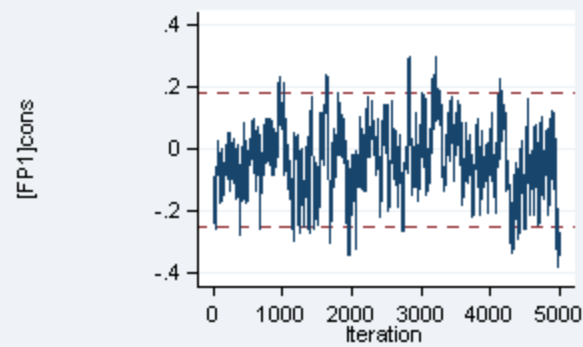
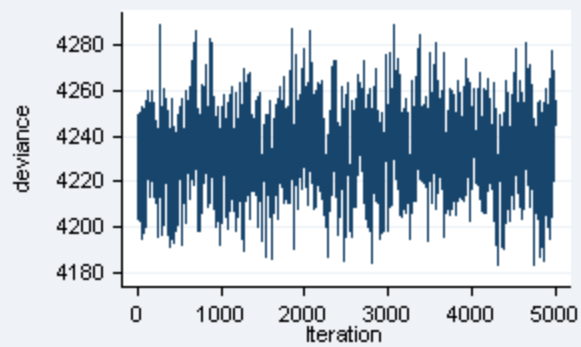
```

MLwin 2.25 multilevel model                Number of obs      =      4059
Binomial logit response model
Estimation algorithm: MCMC
Burnin                =          500
Chain                  =         5000
Thinning               =           1
Run time (seconds)    =         30.1
Deviance (dbar)       =        4232.10
Deviance (thetabar)   =        4159.24
Effective no. of pars (pd) =        72.86
Bayesian DIC          =        4304.96

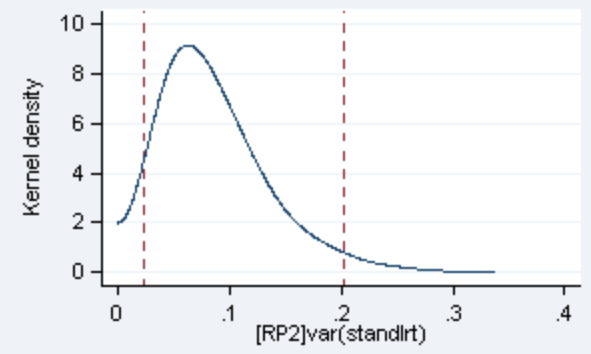
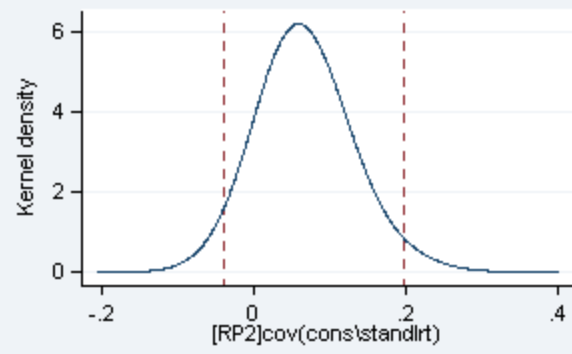
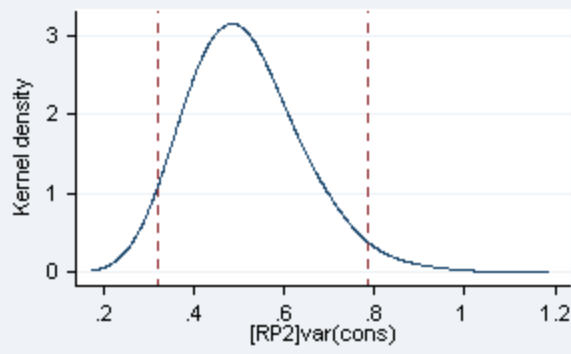
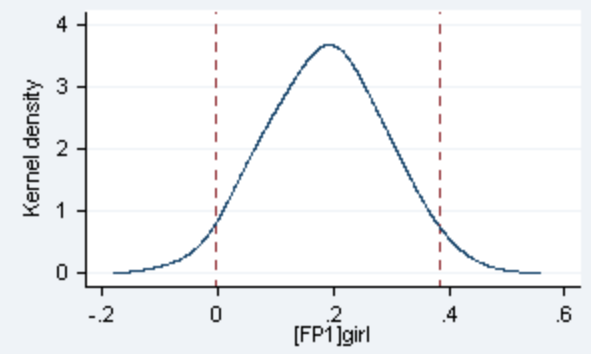
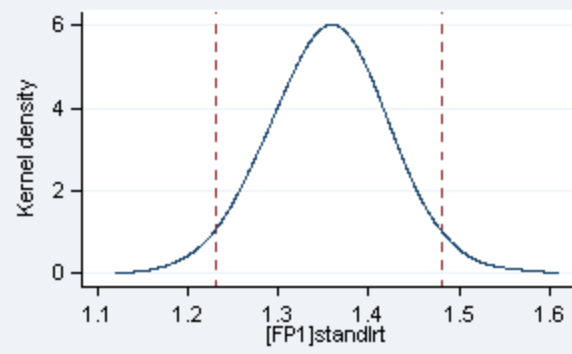
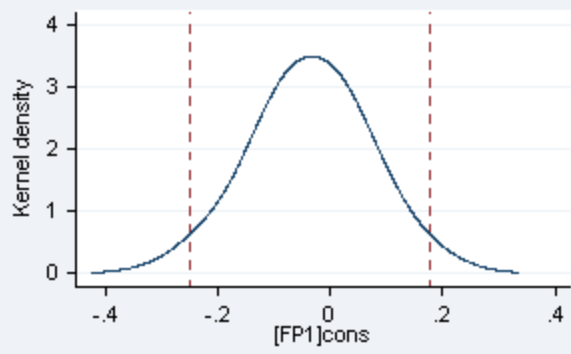
```

passexam	Mean	Std. Dev.	ESS	P	[95% Cred. Interval]	
cons	-.0347943	.1073479	94	0.381	-.2506524	.1779318
standlrt	1.35652	.0624149	496	0.000	1.231931	1.480608
girl	.1873172	.1005095	196	0.026	-.0023705	.3851183

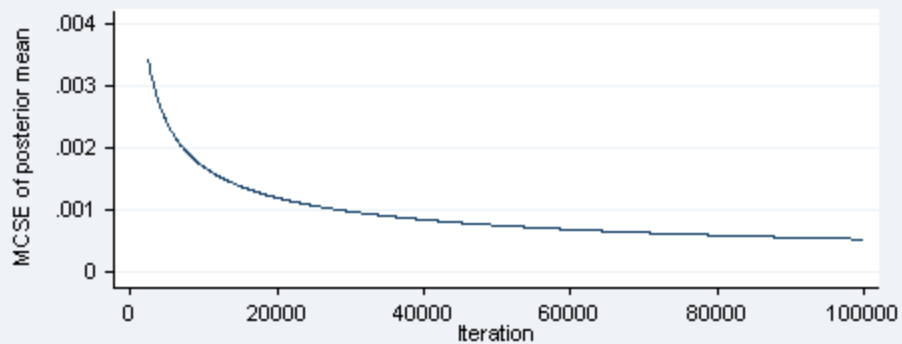
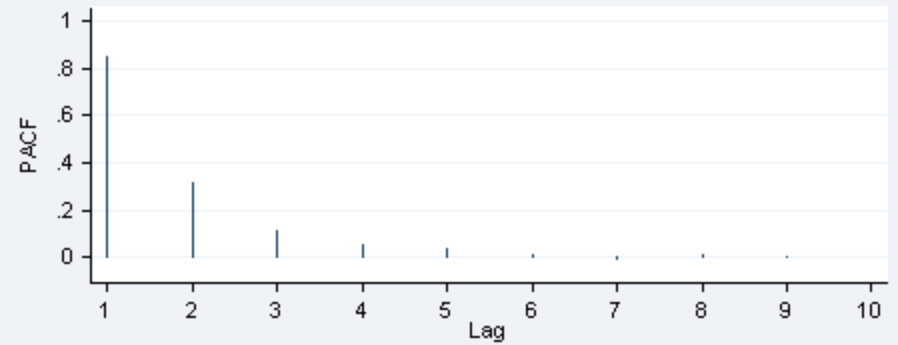
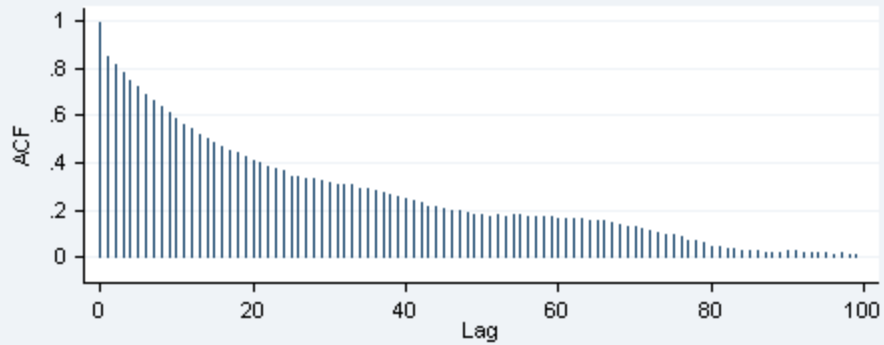
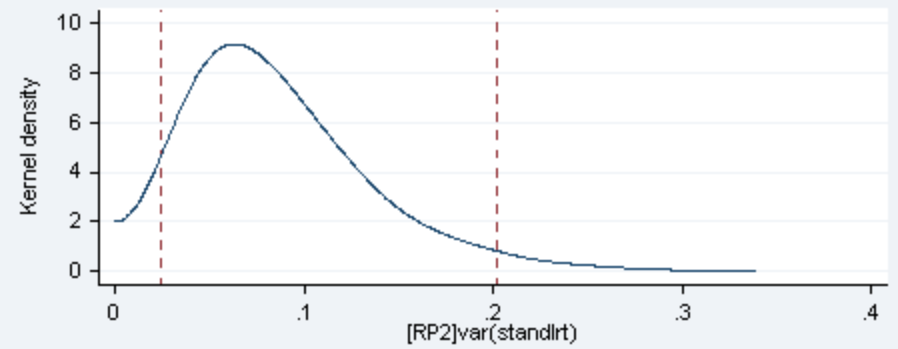
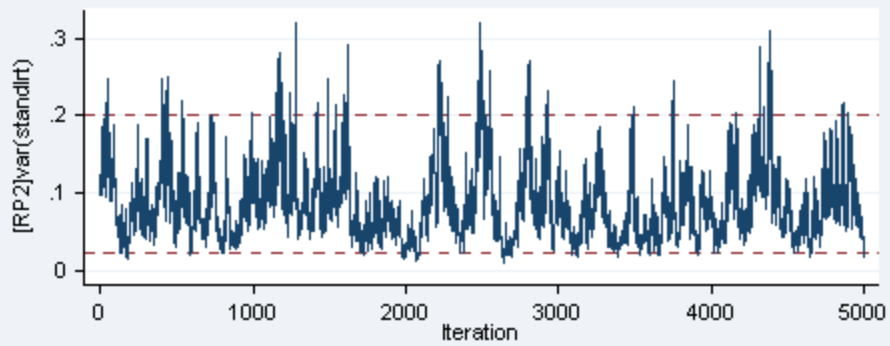
Random-effects Parameters	Mean	Std. Dev.	ESS	[95% Cred. Int]	
Level 2: school					
var(cons)	.5135376	.1199011	1030	.3204156	.7835187
cov(cons,standlrt)	.0668458	.0581714	198	-.0387322	.1982548
var(standlrt)	.0862781	.0467082	99	.0243268	.2023509



. mcmcsum, trajectories



```
. mcmcsum, densities
```



```
. mcmcsum [RP2]var(standlrt), fiveplot
```




. runmlwin, nogroup mode or sd correlation

```

MLwin 2.25 multilevel model           Number of obs       =       4059
Binomial logit response model
Estimation algorithm: MCMC
Burnin                               =           500
Chain                                 =          5000
Thinning                              =             1
Run time (seconds)                   =           30.2
Deviance (dbar)                      =          4232.10
Deviance (thetabar)                  =          4159.24
Effective no. of pars (pd)           =           72.86
Bayesian DIC                          =          4304.96

```

passexam	Odds Ratio	Std. Dev.	ESS	P	[95% Cred. Interval]	
cons	.9579759	.1042228	93	0.381	.7782928	1.194744
standlrt	3.884481	.2435176	497	0.000	3.427844	4.395619
girl	1.205355	.122038	195	0.026	.9976324	1.469788

Random-effects Parameters	Mode	Std. Dev.	ESS	[95% Cred. Int]	
Level 2: school					
sd(cons)	.7030943	.0822202	1013	.5660527	.8851659
corr(cons,standlrt)	.3872765	.2455501	210	-.2034665	.7475395
sd(standlrt)	.2642264	.0760582	91	.1559704	.4498343

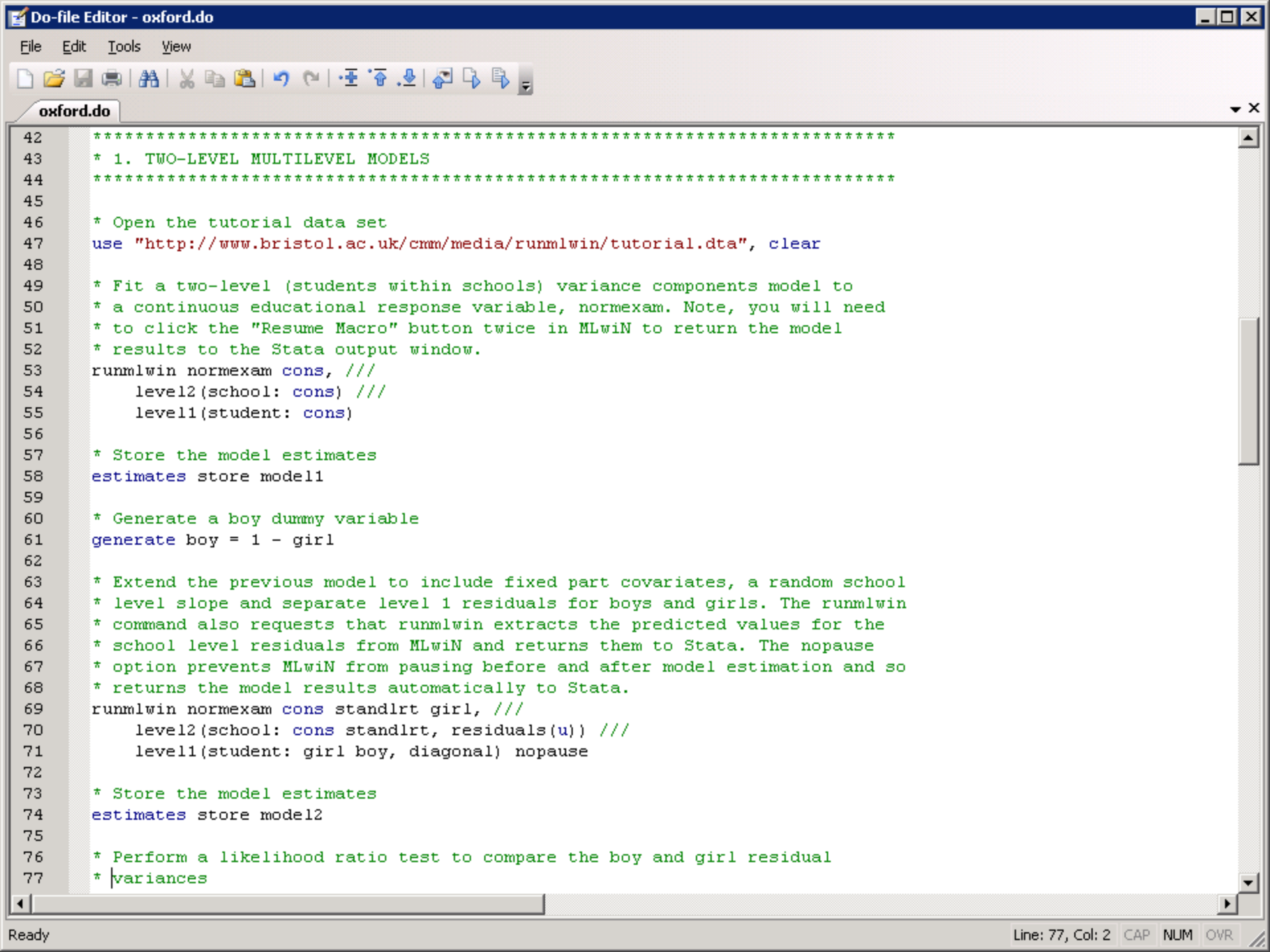
.
.

5. MORE COMPLEX ANALYSES

Five interesting extensions

1. Use `runmlwin` to quickly obtain approximate quasiliikelihood estimates for discrete response models; then finish off estimation using adaptive quadrature in `gllamm`
2. Use `runmlwin` to fit “disease mapping” spatial multilevel models and then plot thematic maps of the area-level residuals using the `spmap` command
3. After fitting model by MCMC using `runmlwin`, use `mcmcsum` to pull back MCMC chains in order to derive posterior distribution for any function of the parameters and data of interest
4. Use the `realcomimpute` command to generate multiply imputed data sets; then use the `runmlwin` command with the `mi estimate` prefix to fit the model of interest to each data set and to combine results using “Rubin’s rules”
5. Use `runmlwin` to generate WinBUGS model, data and initial values files for any MLwiN MCMC model; then fit the model in WinBUGS using the `winbugs` command; then interpret chains using the `mcmcsum` command

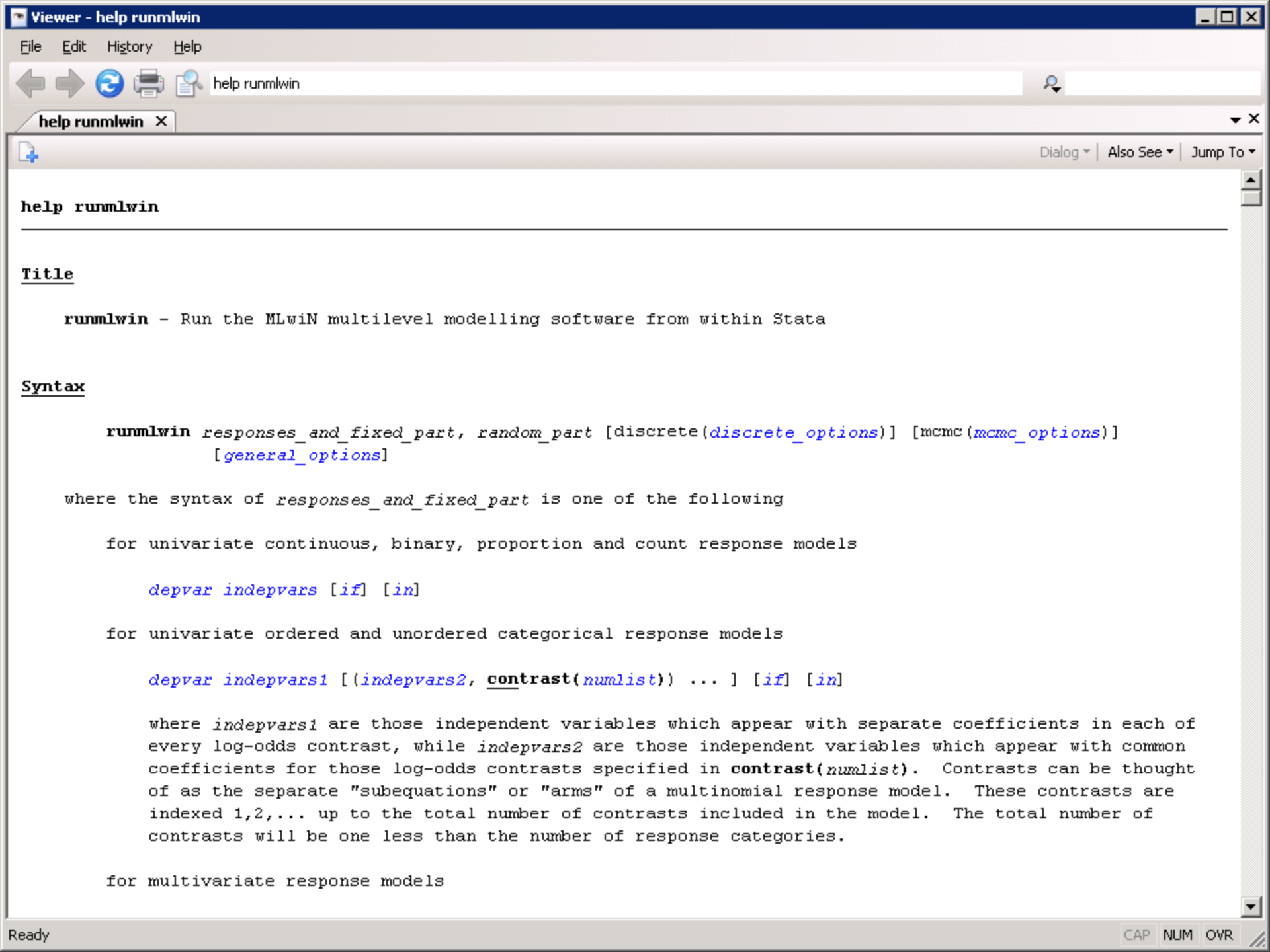
6. STATA MAKES IT EASY TO WORK EFFICIENTLY



oxford.do

```
42 *****
43 * 1. TWO-LEVEL MULTILEVEL MODELS
44 *****
45
46 * Open the tutorial data set
47 use "http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial.dta", clear
48
49 * Fit a two-level (students within schools) variance components model to
50 * a continuous educational response variable, normexam. Note, you will need
51 * to click the "Resume Macro" button twice in MLwiN to return the model
52 * results to the Stata output window.
53 runmlwin normexam cons, ///
54     level2(school: cons) ///
55     level1(student: cons)
56
57 * Store the model estimates
58 estimates store model1
59
60 * Generate a boy dummy variable
61 generate boy = 1 - girl
62
63 * Extend the previous model to include fixed part covariates, a random school
64 * level slope and separate level 1 residuals for boys and girls. The runmlwin
65 * command also requests that runmlwin extracts the predicted values for the
66 * school level residuals from MLwiN and returns them to Stata. The nopause
67 * option prevents MLwiN from pausing before and after model estimation and so
68 * returns the model results automatically to Stata.
69 runmlwin normexam cons standlrt girl, ///
70     level2(school: cons standlrt, residuals(u)) ///
71     level1(student: girl boy, diagonal) nopause
72
73 * Store the model estimates
74 estimates store model2
75
76 * Perform a likelihood ratio test to compare the boy and girl residual
77 * variances
```

7. RESOURCES TO HELP YOU LEARN `runmlwin`



help runmlwin

Title

`runmlwin` - Run the MLwiN multilevel modelling software from within Stata

Syntax

```
runmlwin responses_and_fixed_part, random_part [discrete(discrete_options)] [mcmc(mcmc_options)]  
[general_options]
```

where the syntax of `responses_and_fixed_part` is one of the following

for univariate continuous, binary, proportion and count response models

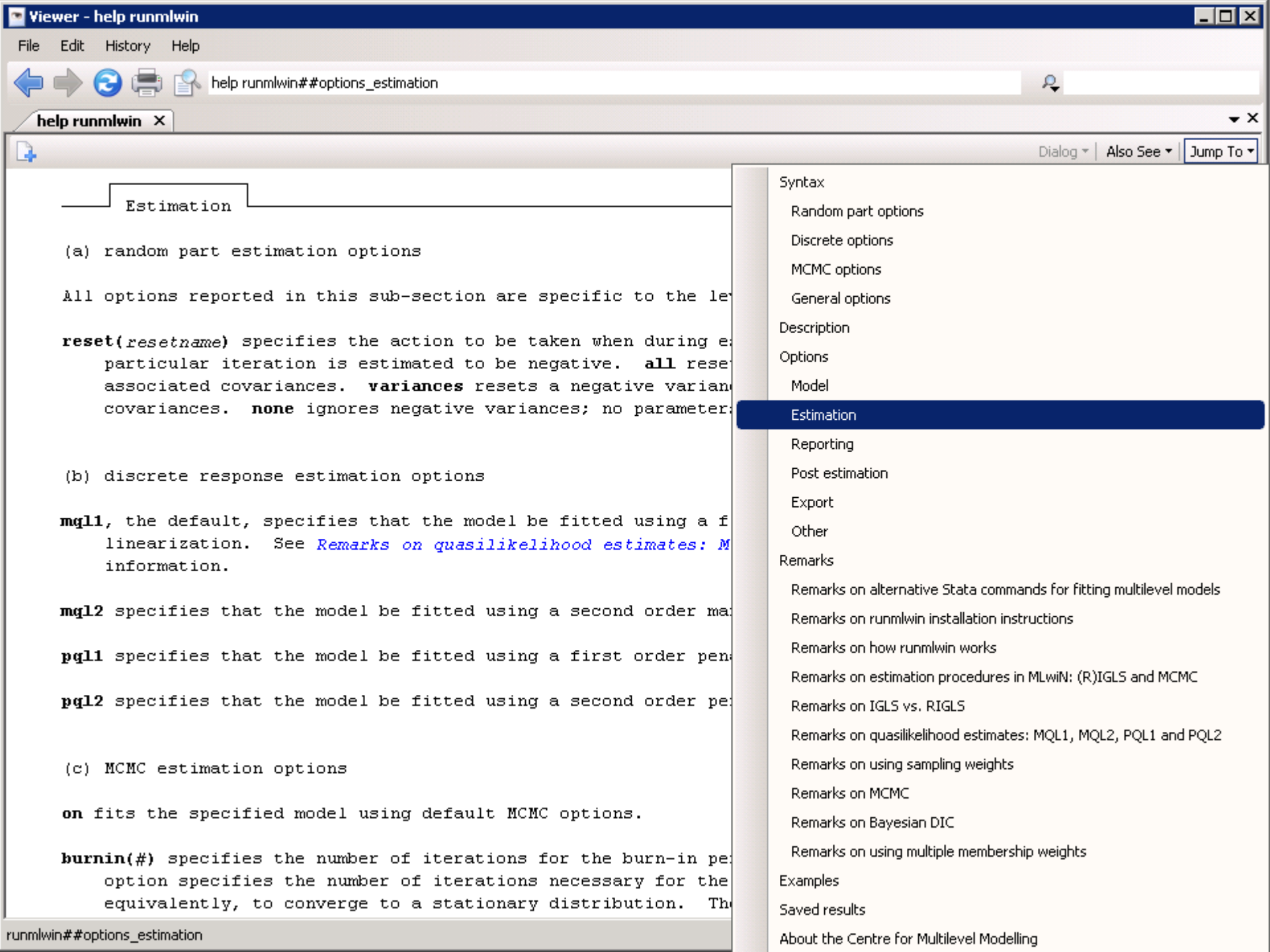
```
depvar indepvars [if] [in]
```

for univariate ordered and unordered categorical response models

```
depvar indepvars1 [(indepvars2, contrast(numlist)) ... ] [if] [in]
```

where `indepvars1` are those independent variables which appear with separate coefficients in each of every log-odds contrast, while `indepvars2` are those independent variables which appear with common coefficients for those log-odds contrasts specified in `contrast(numlist)`. Contrasts can be thought of as the separate "subequations" or "arms" of a multinomial response model. These contrasts are indexed 1,2,... up to the total number of contrasts included in the model. The total number of contrasts will be one less than the number of response categories.

for multivariate response models



Estimation

(a) random part estimation options

All options reported in this sub-section are specific to the level of estimation.

reset(resetname) specifies the action to be taken when during estimation a particular iteration is estimated to be negative. **all** resets all associated covariances. **variances** resets a negative variance to zero. **none** ignores negative variances; no parameter is estimated.

(b) discrete response estimation options

mq11, the default, specifies that the model be fitted using a first order linearization. See [Remarks on quaslikelihood estimates: MQL1](#) for more information.

mq12 specifies that the model be fitted using a second order method.

pq11 specifies that the model be fitted using a first order perturbation method.

pq12 specifies that the model be fitted using a second order perturbation method.

(c) MCMC estimation options

on fits the specified model using default MCMC options.

burnin(#) specifies the number of iterations for the burn-in period. The **burnin** option specifies the number of iterations necessary for the model to converge equivalently, to converge to a stationary distribution. The **burnin** option is only used when the **on** option is used.

- Syntax
- Random part options
- Discrete options
- MCMC options
- General options
- Description
- Options
- Model
- Estimation**

- Reporting
- Post estimation
- Export
- Other
- Remarks
 - Remarks on alternative Stata commands for fitting multilevel models
 - Remarks on runmlwin installation instructions
 - Remarks on how runmlwin works
 - Remarks on estimation procedures in MLwiN: (R)IGLS and MCMC
 - Remarks on IGLS vs. RIGLS
 - Remarks on quaslikelihood estimates: MQL1, MQL2, PQL1 and PQL2
 - Remarks on using sampling weights
 - Remarks on MCMC
 - Remarks on Bayesian DIC
 - Remarks on using multiple membership weights

- Examples
- Saved results
- About the Centre for Multilevel Modelling

Examples

IMPORTANT. The following examples will only work on your computer once you have installed MLwiN and once you have told `runmlwin` what the `mlwin.exe` file address is. See [Remarks on runmlwin installation instructions](#) above for more information.

(a) Continuous response models

Two-level models

Setup

```
. use http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial, clear
```

Two-level random-intercept model, analogous to `xtreg` (fitted using IGLS)

(See page 28 of the *MLwiN User Manual*)

```
. runmlwin normexam cons standlrt, level2(school: cons) level1(student: cons) nopause
```

Two-level random-intercept and random-slope (coefficient) model (fitted using IGLS)

(See page 59 of the *MLwiN User Manual*)

```
. runmlwin normexam cons standlrt, level2 (school: cons standlrt) level1 (student: cons) nopause
```

Refit the model, where this time we additionally calculate the level 2 residuals (fitted using IGLS)

(See page 59 of the *MLwiN User Manual*)

```
. runmlwin normexam cons standlrt, level2 (school: cons standlrt, residuals(u)) level1 (student: cons) nopause
```

Two-level random-intercept and random-slope (coefficient) model with a complex level 1 variance function (fitted using IGLS)

(See page 99 of the *MLwiN User Manual*)

```
. matrix A = (1,1,0,0,0,1)
. runmlwin normexam cons standlrt girl, level2(school: cons standlrt) level1(student: cons standlrt girl, elements(A)) nopause
```

Bristol University | Centre for Multilevel Modelling | runmlwin: Running MLwiN from within Stata - Mozilla Firefox

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www.bristol.ac.uk/cmm/software/runmlwin/

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- runmlwin**
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runmlwin: Running MLwiN from within Stata

runmlwin is a Stata command which allows Stata users to run the powerful MLwiN multilevel modelling software from within Stata.

The multilevel models fitted by **runmlwin** are often considerably faster than those fitted by the Stata's **xtmixed**, **xtmlogit** and **xtmepoisson** commands. The range of models which can be fitted by **runmlwin** is also much wider than those commands. **runmlwin** also allows fast estimation on large data sets for many of the more complex multilevel models available through the user written **gllamm** command.

MLwiN has the following features:

1. Estimation of multilevel models for continuous, binary, count, ordered categorical and unordered categorical data
2. Fast estimation via classical and Bayesian methods
3. Estimation of multilevel models for cross-classified and multiple membership nonhierarchical data structures
4. Estimation of multilevel multivariate response models, multilevel spatial models, multilevel measurement error models and multilevel multiple imputation models

These details with a screen shot are available on our **runmlwin** [leaflet](#) (pdf, 0.1mb)

Presentations

We have provided a range of presentations showcasing **runmlwin**. These presentations provide a quick overview of how the command works and the range of models which can be fitted. [More >>](#)

Installation



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- MLwiN
- Realcom
- MLPowSim
- runmlwin
- Presentations**
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Presentations using runmlwin

- 5th ESRC Research Methods Festival, Oxford (3rd July 2012)
 - [Slides](#) (PDF, 2.0mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- UK Stata Users' Group, 17th Meeting (16th September 2011)
 - [Slides](#) (PDF, 2.0mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- University of Bristol, Mplus/MLwiN User Group (MUGS) meeting (14th June 2011)
 - [Slides](#) (PDF, 2.3mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- Modern Modeling Methods (M3) Conference, University of Connecticut (26th May 2011)
 - [Slides](#) (PDF, 3.2mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- 2011 American Sociological Association Spring Methodology Conference, Tilburg University (20th May 2011)
 - [Slides](#) (PDF, 2.0mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- University of Bristol, e-Stat meeting (7th April 2011)



Centre for Multilevel Modelling



SOFTWARE

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Examples using runmlwin

MLwiN User Manual

These do-files and log files replicate the analyses reported in the [MLwiN User Manual](#) (PDF, 4.6 mb) Rasbash, J., Steele, F., Browne, W.J. and Goldstein, H. (2009) Centre for Multilevel Modelling, University of Bristol.

Note that we have not created do-files for Chapters 1, 8 or 19 of the manual as no models are fitted in those chapters. We have also not yet attempted to replicate the analysis in Chapter 17.

- 1 Introducing Multilevel Models
- 2 Introduction to Multilevel Modelling ([do](#) | [log](#))
- 3 Residuals ([do](#) | [log](#))
- 4 Random Intercept and Random Slope Models ([do](#) | [log](#))
- 5 Graphical Procedures for Exploring the Model ([do](#) | [log](#))
- 6 Contextual Effects ([do](#) | [log](#))
- 7 Modelling the Variance as a Function of Explanatory Variables ([do](#) | [log](#))
- 8 Getting Started with your Data
- 9 Logistic Models for Binary and Binomial Responses ([do](#) | [log](#))
- 10 Multinomial Logistic Models for Unordered Categorical Responses ([do](#) | [log](#))
- 11 Fitting an Ordered Category Response Model ([do](#) | [log](#))
- 12 Modelling Count Data ([do](#) | [log](#))
- 13 Fitting Models to Repeated Measures Data ([do](#) | [log](#))
- 14 Multivariate Response Models ([do](#) | [log](#))

runmlwin user forum









Forum rules








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ANNOUNCEMENTS	REPLIES	VIEWS	LAST POST
 runmlwin has had 1300+ downloads since Oct 2011 by GeorgeLeckie » Tue May 15, 2012 8:00 pm	0	315	by GeorgeLeckie  Tue May 15, 2012 8:00 pm
 Make sure you have latest version of runmlwin: 16/04/2012 by GeorgeLeckie » Tue May 01, 2012 4:21 pm	0	329	by GeorgeLeckie  Tue May 01, 2012 4:21 pm
 Do-files to replicate entire MLwin User & MCMC Manuals by GeorgeLeckie » Mon Apr 18, 2011 5:30 pm	7	967	by GeorgeLeckie  Tue Mar 13, 2012 3:47 pm
 Welcome to the runmlwin discussion forum by GeorgeLeckie » Fri Apr 01, 2011 4:06 pm	0	572	by GeorgeLeckie  Fri Apr 01, 2011 4:06 pm

TOPICS	REPLIES	VIEWS	LAST POST
 Errors in estimating 2-level model with random slopes by Jacqueline » Wed Jun 27, 2012 5:08 pm	1	5	by GeorgeLeckie  Wed Jun 27, 2012 5:51 pm
 Predicted probabilities after multilevel logit model by Raphael » Sun Jun 24, 2012 10:08 pm	4	15	by Raphael  Wed Jun 27, 2012 3:37 pm
 Error fitting Multinomial logit using PQL2 by jmflavel » Mon Jun 18, 2012 6:45 am	4	29	by GeorgeLeckie  Mon Jun 25, 2012 6:25 pm
 Errors fitting cross-classified logistic model by MCMC by rebvas86 » Wed May 30, 2012 2:46 pm	6	898	by GeorgeLeckie  Thu Jun 14, 2012 11:29 am
 DIC statistic for multinomial random effects model by bogdan2012 » Mon Jun 04, 2012 9:35 pm	1	263	by GeorgeLeckie  Tue Jun 05, 2012 9:40 am
 Getting p-values and z-ratios after MCMC by AnjaScheiwe » Tue May 22, 2012 11:49 am	4	373	by AnjaScheiwe  Tue May 22, 2012 2:09 pm
 Re: Residuals for multi-level logistic model in runmlwin by DavidPopMed » Mon May 14, 2012 7:03 pm	1	249	by GeorgeLeckie  Mon May 14, 2012 7:29 pm
 Problem getting residuals: after merge, not all observations by ewancarr » Tue May 01, 2012 9:34 pm	10	566	by ewancarr  Thu May 03, 2012 7:09 pm
 discrete time multilevel event history model	-	...	by ChrisCharlton 