

Running MLwiN from within Stata: the `runmlwin` command

CCSR/ISC Seminar series
Manchester
25th September 2012

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University of Bristol

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...
 - Then use the `R2MLwiN` R function to run MLwiN from within R (see later)
 - `R2MLwiN` provides all 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 very slow
- Other user-written multilevel modelling commands available in Stata 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

Outline

1. Continuous response models
2. Working efficiently
3. Binary response models
4. Simulation studies
5. MCMC estimation
6. Export models to WinBUGS
7. Speed comparisons
8. More complex analyses
9. Resources to help you learn `runmlwin`
10. Running MLwiN from within R: the `R2MLwiN` function

1. CONTINUOUS RESPONSE MODELS

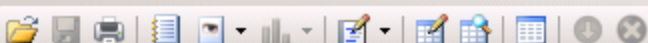
Two-level variance components model

- 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
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 4905 Lakeway Drive
 College Station, Texas 77845 USA
 800-STAT-PC <http://www.stata.com>
 979-696-4600 stata@stata.com
 979-696-4601 (fax)

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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	

Command



STATA (R)
Statistics/Data Analysis

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Variables ↑ ↓ ×

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

There are no items to show.

Properties ↑ ↓ ×


Variables

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>

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...

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

The `runmlwin` command syntax

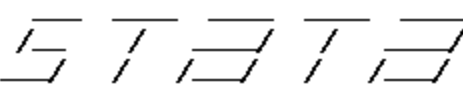
$$\mathbf{normexam}_{ij} = \beta_0 + u_j + e_{ij}$$

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

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

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





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

.

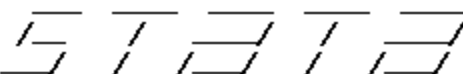
Variable	Label
school	School ID
student	Student ID
normexam	Age 16 exam score...
cons	Constant
standlrt	Age 11 exam score...
girl	Girl
schgend	School gender
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Variables	
Name	school
Label	School ID
Type	byte
Format	%9.0g
Value Label	
Notes	

Command

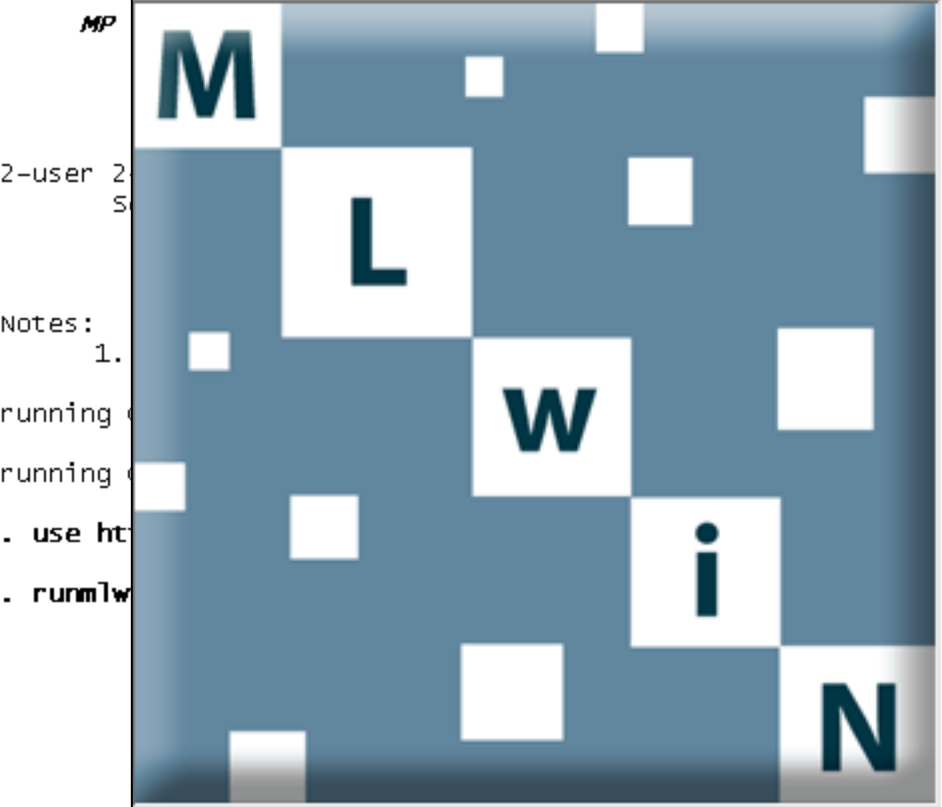
runmlwin normexam cons, level2[school: cons] level1[student: cons]



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 StataCorp
 4905 Lakeway Drive

Variables

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.

Command

Variables

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

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

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

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

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

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

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



```
. 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
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girl	Girl
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Properties	
Name	school
Label	School ID
Type	byte
Format	%9.0g
Value Label	
Notes	



```
. runmlwin normexam cons, level2(school: cons) level1(student: cons)
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```
MLwin 2.25 multilevel model           Number of obs       =       4059
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Level Variable	No. of Groups	Observations per Group		
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school	65	2	62.4	198

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Run time (seconds) =      17.13
Number of iterations =      3
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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

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

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

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

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

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

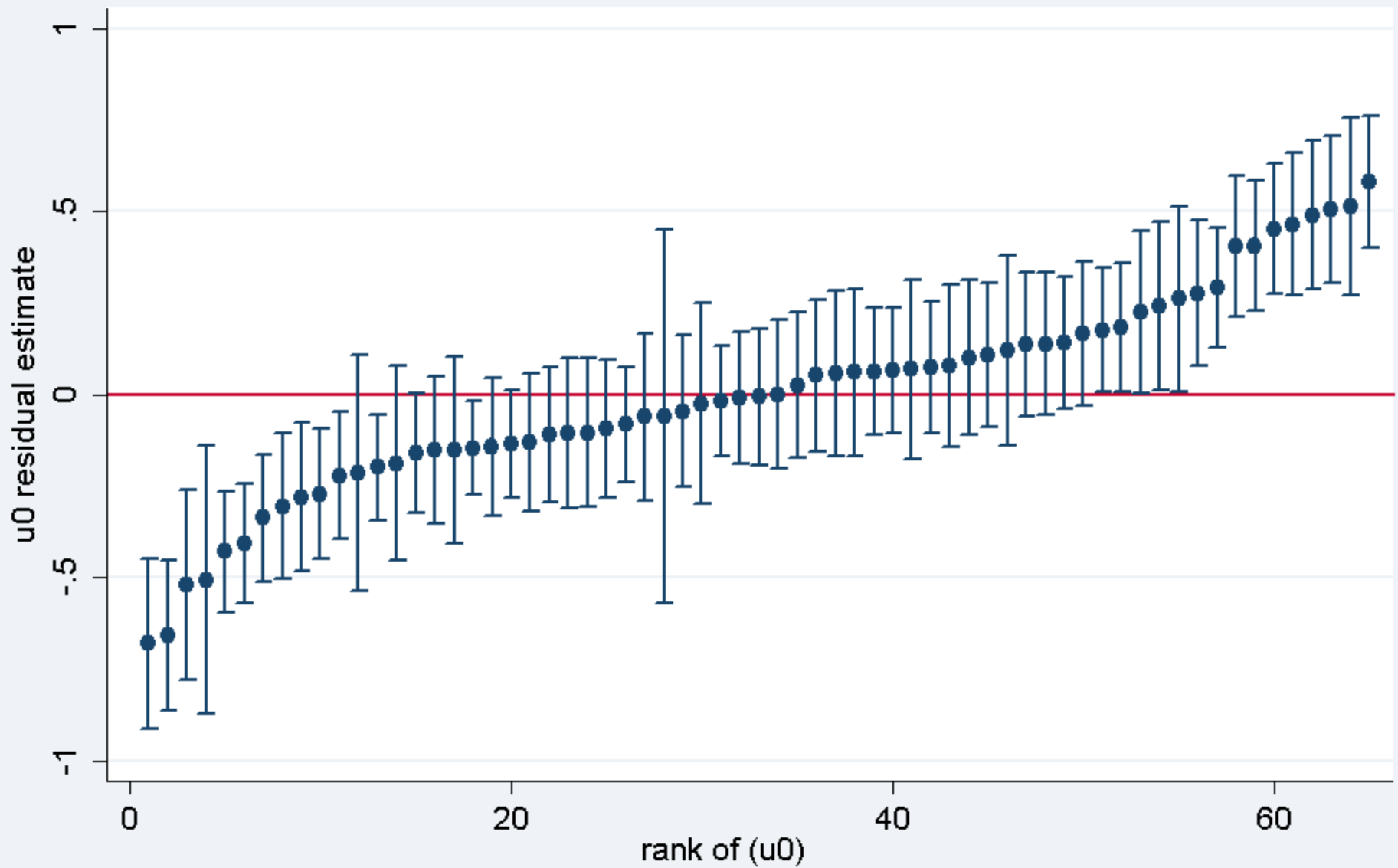
```

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

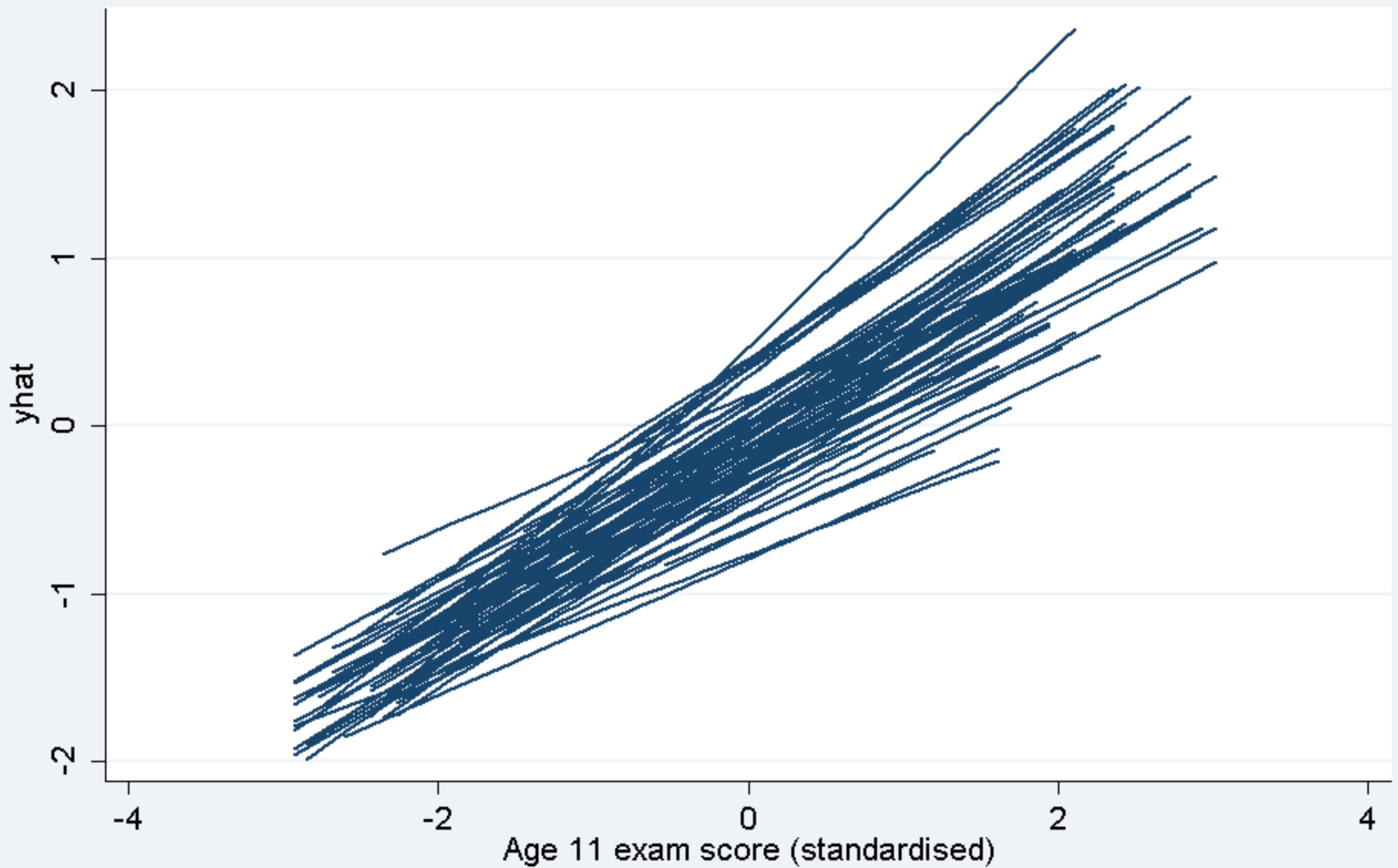
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level 2: school				
var(cons)	.0862511	.017175	.0525887	.1199135
cov(cons,standlrt)	.0190537	.0066789	.0059632	.0321441
var(standlrt)	.0148919	.0044702	.0061304	.0236534
Level 1: student				
var(girl)	.5251641	.0152836	.4952088	.5551194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

Variables T ↑ ×

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. STATA MAKES IT EASY TO WORK EFFICIENTLY

File Edit Tools View



Manchester.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
```

3. BINARY RESPONSE MODELS

Random slope logistic model

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

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

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

```
. 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

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

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

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

```
. 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

.
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4. 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
```

5. MCMC ESTIMATION

Random slope logistic model

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

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

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

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

```

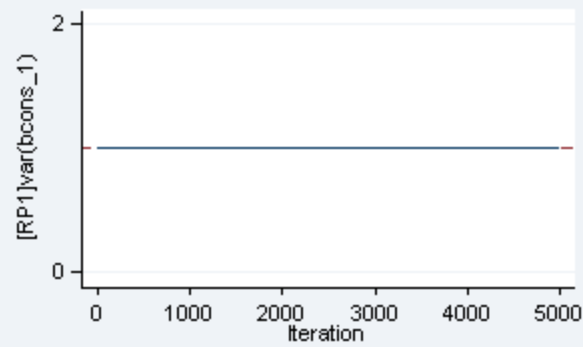
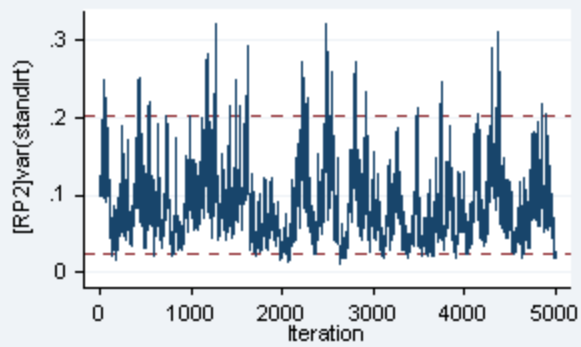
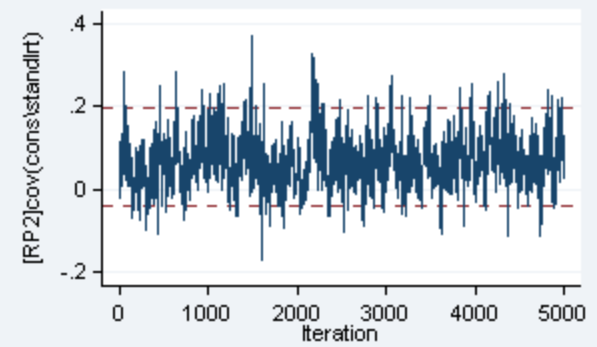
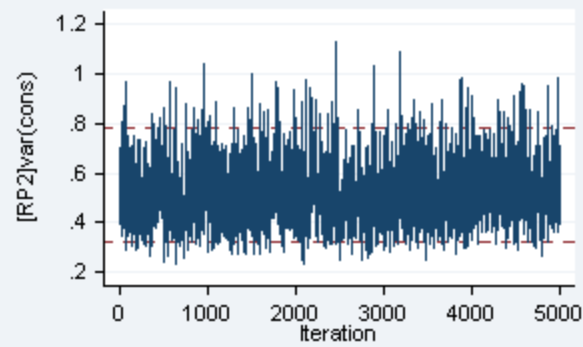
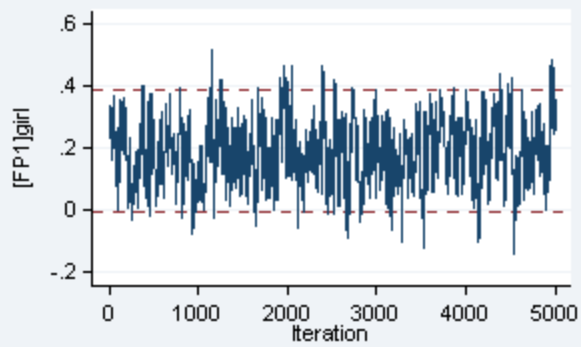
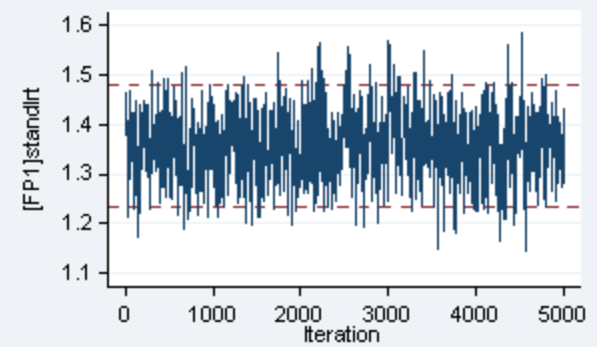
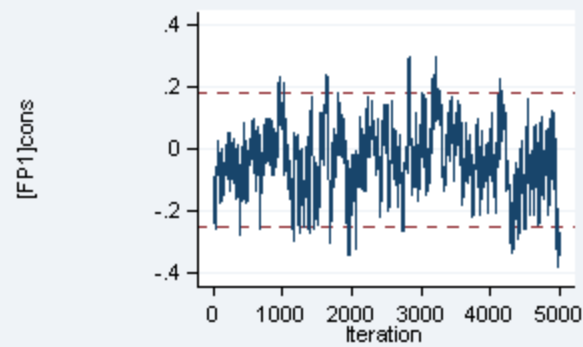
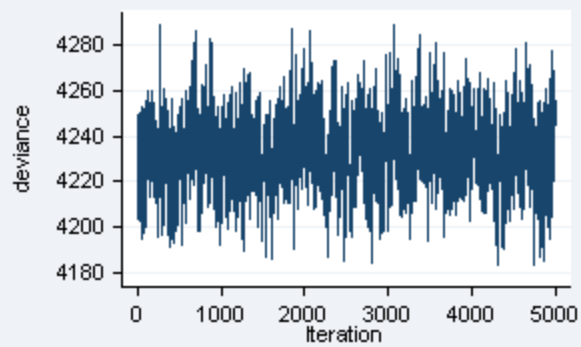
```

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

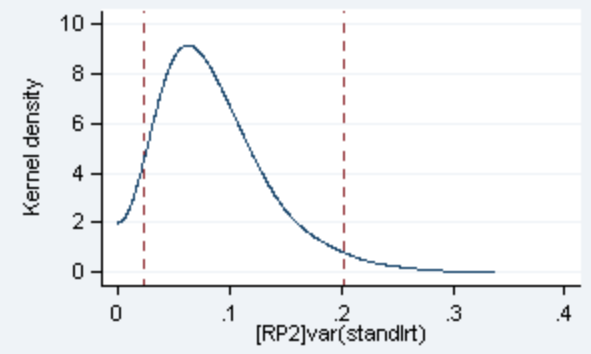
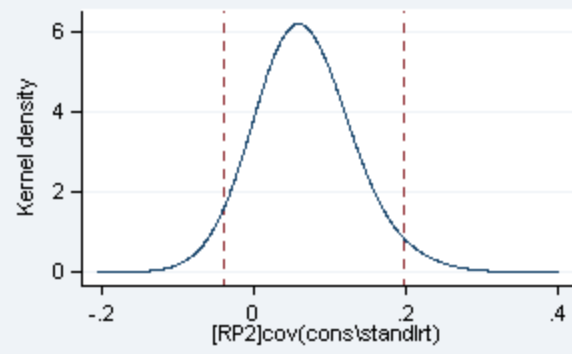
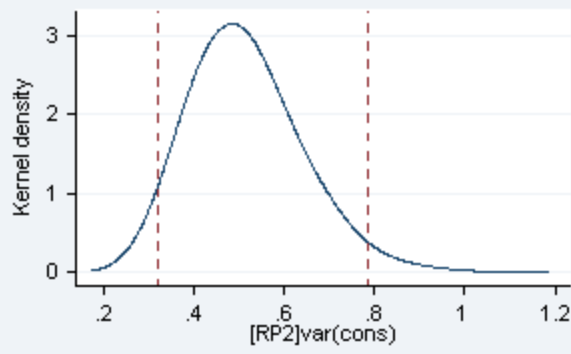
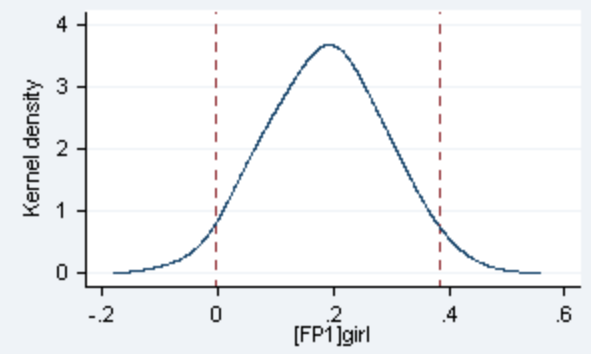
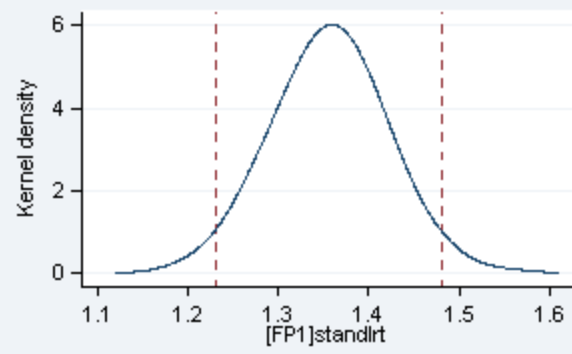
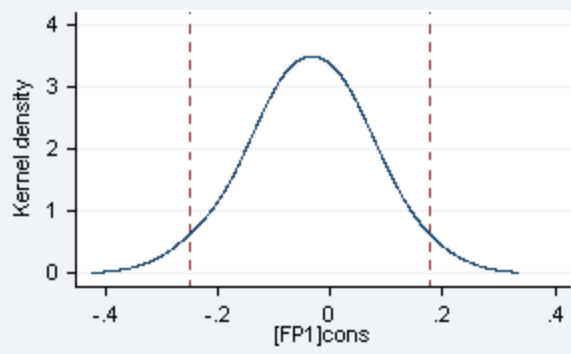
```

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

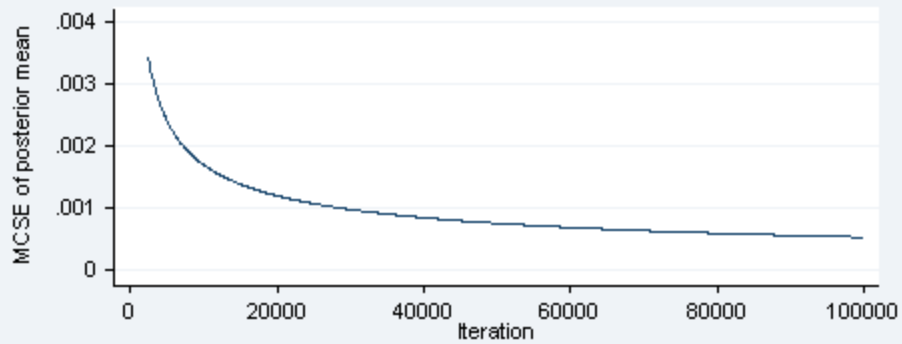
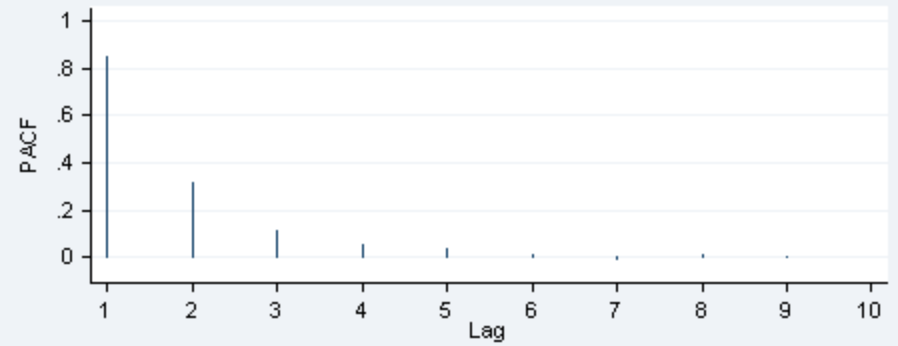
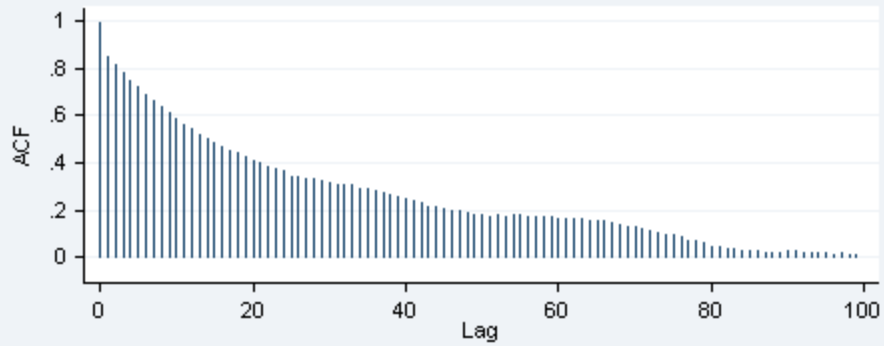
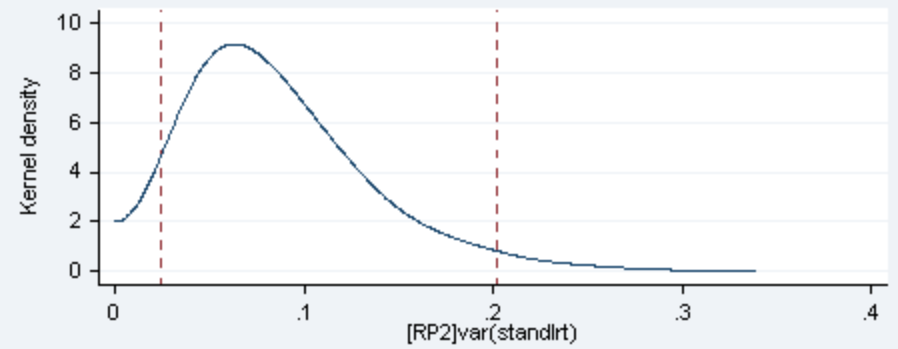
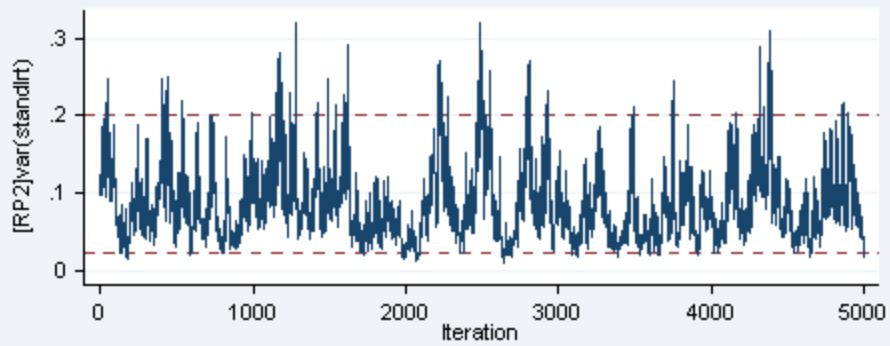
Random-effects Parameters	Mean	Std. Dev.	ESS	[95% Cred. Int]	
Level 2: school					
var(cons)	.5135376	.1199011	1030	.3204156	.7835187
cov(cons,standlrt)	.0668458	.0581714	198	-.0387322	.1982548
var(standlrt)	.0862781	.0467082	99	.0243268	.2023509



. mcmcsun, trajectories



```
. mcmcsum, densities
```



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



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

```
[RP2]var(standlrt)
```

Percentiles

Mean	.0862781		0.5%	.0193246	Thinned Chain Length	5000
MCSE of Mean	.0024099		2.5%	.0243268	Effective Sample Size	99
Std. Dev.	.0467082		5%	.0298808	Raftery Lewis (2.5%)	25770
Mode	.0631075		25%	.0520173	Raftery Lewis (97.5%)	23976
P(mean)	0				Brooks Draper (mean)	446390
P(mode)	0	50%		.0765091		
P(median)	0		75%	.1100566		
			95%	.179421		
			97.5%	.2023509		
			99.5%	.2549108		

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. 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

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 .

6. EXPORT MODELS TO WinBUGS

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) l(logit) de(cons)) ///  
  mcmc(b(500) c(5000) savewinbugs(model(m.txt)  
  inits(i.txt) data(d.txt) nofit)) ///  
  initsprevious nogroup nopause
```

```
Viewer - view m.txt
File Edit History Help
view m.txt
view m.txt x
Dialog | Also See | Jump To
# WINBUGS 1.4 code generated from MLwiN program
#----MODEL Definition-----

model
{
# Level 1 definition
for(i in 1:N) {
passexam[i] ~ dbin(p[i],denom[i])
logit(p[i]) <- beta[1] * cons[i]
+ beta[2] * standlrt[i]
+ beta[3] * girl[i]
+ u2[school[i],1] * cons[i]
+ u2[school[i],2] * standlrt[i]
}
# Higher level definitions
for (j in 1:n2) {
u2[j,1:2] ~ dnorm(zero2[1:2],tau.u2[1:2,1:2])
}
# Priors for fixed effects
for (k in 1:3) { beta[k] ~ dflat() }
# Priors for random terms
for (i in 1:2) {zero2[i] <- 0}
tau.u2[1:2,1:2] ~ dwish(R2[1:2, 1:2],2)
sigma2.u2[1:2,1:2] <- inverse(tau.u2[,])
}

Ready CAP NUM OVR
```


7. SPEED COMPARISONS

runmlwin vs. xtmixed

- Simulated data: 130,000 students in 650 schools (200 students per school)

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

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

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

Software method	Seconds	β_0	β_1	β_2	σ_{u0}^2	σ_{u01}	σ_{u1}^2	σ_{e2}^2	σ_{e3}^2
True values	—	0.00	0.50	0.20	0.10	0.00	0.05	0.50	0.60
runmlwin	6	-0.01	0.50	0.20	0.10	0.01	0.05	0.50	0.60
xtmixed	158	-0.01	0.50	0.20	0.10	0.01	0.05	0.50	0.60

runmlwin vs. xtmeologit

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

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

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

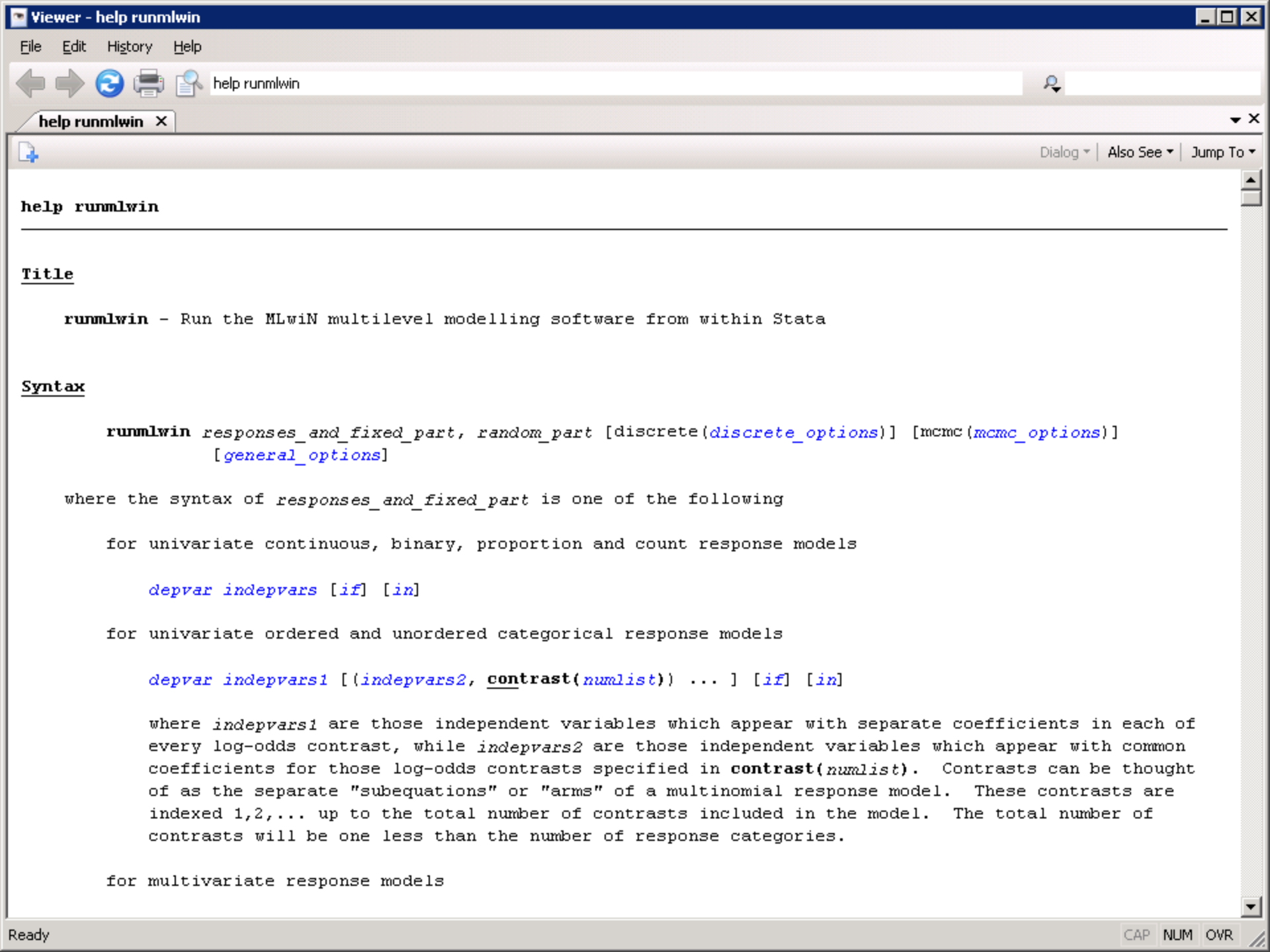
Software method	Seconds	β_0	β_1	β_2	σ_{u0}^2	σ_{u01}	σ_{u1}^2
True values	—	0.00	1.50	0.20	0.50	0.00	0.10
runmlwin, mql1	9	-0.01	1.32	0.18	0.40	0.00	0.13
runmlwin, pql2	14	-0.01	1.49	0.20	0.50	-0.00	0.12
runmlwin, b(200) c(1000)	313	0.00	1.49	0.21	0.50	-0.00	0.11
runmlwin, b(500) c(5000)	310	0.00	1.49	0.21	0.50	-0.00	0.11
xtmeologit, intpoints(1)	265	-0.01	1.49	0.20	0.50	-0.00	0.11
xtmeologit, intpoints(7)	451	-0.01	1.49	0.20	0.50	-0.00	0.12

8. 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 (e.g. ICC or ranks of random effects)
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

9. 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

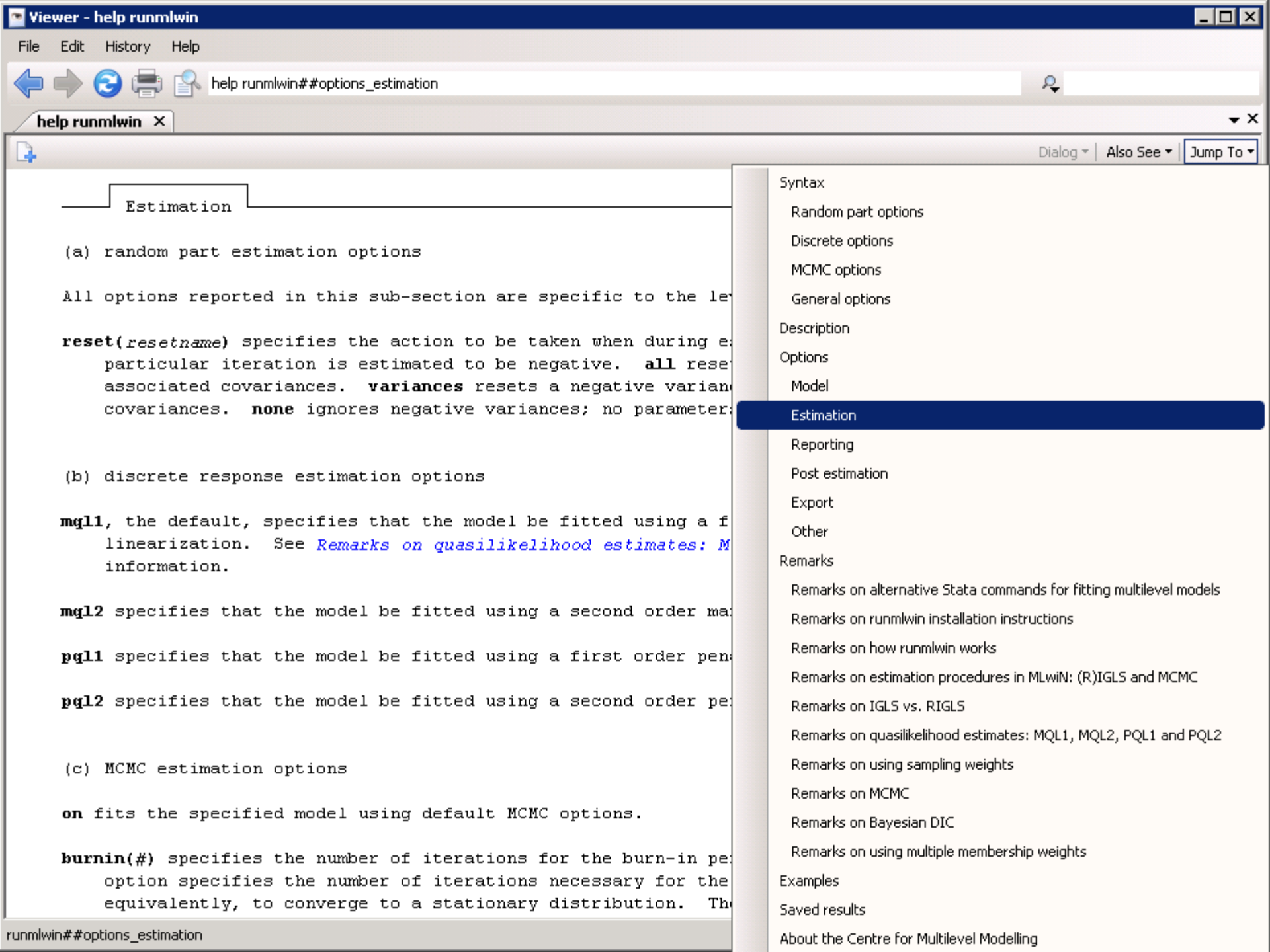
```
depvar indepvars [if] [in]
```

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 quasiliikelihood 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 quasiliikelihood 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
```



Centre for Multilevel Modelling



SOFTWARE

MLwiN
Realcom
Stat-JR
MLPowSim
R2MLwiN

runmlwin

- Presentations
- Examples
- Citations
- User Forum

[CMM software support](#)[University home](#) > [Centre for Multilevel Modelling...](#) > [Software](#) > [runmlwin](#) **runmlwin: Running MLwiN from within Stata**

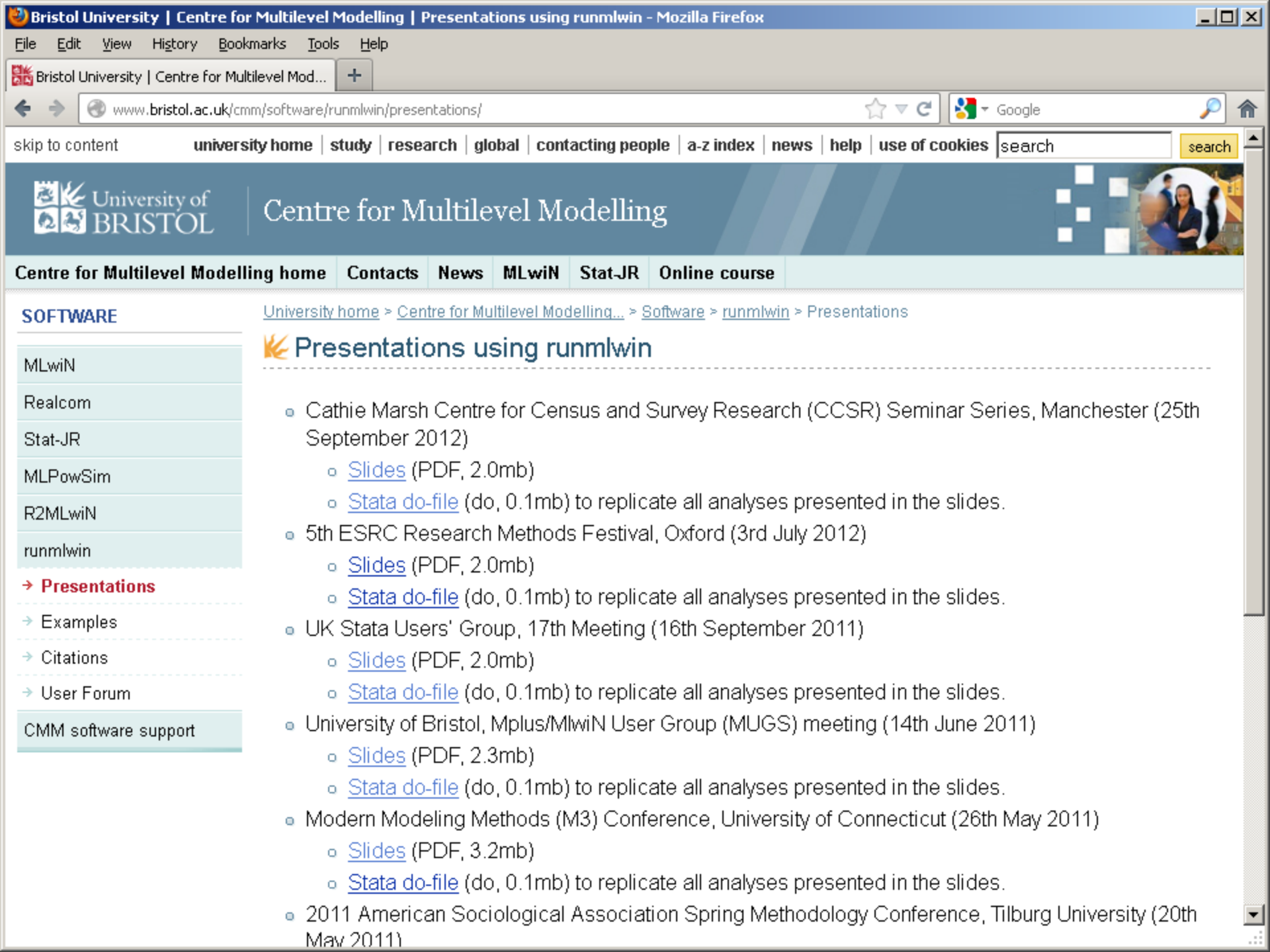
runmlwin is a Stata command which allows Stata users to run the powerful MLwiN multilevel modelling software from within Stata.

The multilevel models fitted by **runmlwin** are often considerably faster than those fitted by the Stata's **xtmixed**, **xtmelogit** 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)



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Presentations using runmlwin

- Cathie Marsh Centre for Census and Survey Research (CCSR) Seminar Series, Manchester (25th September 2012)
 - [Slides](#) (PDF, 2.0mb)
 - [Stata do-file](#) (do, 0.1mb) to replicate all analyses presented in the slides.
- 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)



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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](#))

runmlwin user forum









Forum rules















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96 topics • Page 1 of 4 • 1 2 3 4

ANNOUNCEMENTS	REPLIES	VIEWS	LAST POST
 runmlwin has had 2300+ downloads since Oct 2011 by GeorgeLeckie » Tue May 15, 2012 7:00 pm	0	1009	by GeorgeLeckie  Tue May 15, 2012 7:00 pm
 Make sure you have latest version of runmlwin: 16/04/2012 by GeorgeLeckie » Tue May 01, 2012 3:21 pm	0	1111	by GeorgeLeckie  Tue May 01, 2012 3:21 pm
 Do-files to replicate entire MLwiN User & MCMC Manuals by GeorgeLeckie » Mon Apr 18, 2011 4:30 pm	7	2131	by GeorgeLeckie  Tue Mar 13, 2012 2:47 pm
 Welcome to the runmlwin discussion forum by GeorgeLeckie » Fri Apr 01, 2011 3:06 pm	0	1195	by GeorgeLeckie  Fri Apr 01, 2011 3:06 pm

TOPICS	REPLIES	VIEWS	LAST POST
 trouble fitting cross-classified model by katetilling » Tue Sep 18, 2012 7:43 am	3	25	by katetilling  Tue Sep 18, 2012 6:49 pm
 error in multiple membership models by morning03 » Thu Sep 13, 2012 5:45 am	4	34	by morning03  Sun Sep 16, 2012 4:34 am
 Spatial multilevel models by Raphael » Wed Sep 12, 2012 10:00 pm	2	13	by Raphael  Fri Sep 14, 2012 3:25 am
 signs of covariates change using multiple membership model by morning03 » Fri Sep 07, 2012 4:02 am	1	26	by GeorgeLeckie  Mon Sep 10, 2012 4:57 pm
 can't proceed to multiple membership model by morning03 » Wed Aug 22, 2012 4:25 am	3	61	by GeorgeLeckie  Thu Aug 23, 2012 10:17 am
 Gamma Regression with random effects by AndreasHaupt » Mon Aug 13, 2012 11:03 am	2	41	by AndreasHaupt  Mon Aug 13, 2012 11:37 am
 Significance of random effects in cross-classified model by AnjaScheiwe » Sun Aug 12, 2012 1:36 am	2	42	by AnjaScheiwe  Mon Aug 13, 2012 10:02 am



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runmlwin: A Program to Run the MLwiN Multilevel Modelling Software from within Stata

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Abstract

We illustrate how to fit multilevel models in the MLwiN package seamlessly from within Stata using the Stata program `runmlwin`. We argue that using MLwiN and Stata in combination allows researchers to capitalise on the best features of both packages. We provide examples of how to use `runmlwin` to fit continuous, binary, ordinal, nominal and mixed response multilevel models by both maximum likelihood and Markov chain Monte Carlo estimation.

Keywords: `runmlwin`, MLwiN, Stata, multilevel model, random effects model, mixed model, hierarchical linear model, clustered data, maximum likelihood estimation, Markov chain Monte Carlo estimation.

10. RUN MLwiN FROM WITHIN R: THE R2MLwiN FUNCTION

Continuous and binary response random slope models

- Continuous response model

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

$$\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{pmatrix} \right\}, \quad \begin{pmatrix} e_{2ij} \\ e_{3ij} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{e2}^2 & \\ 0 & \sigma_{e3}^2 \end{pmatrix} \right\}$$

- Binary response model

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

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

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

RStudio

File Edit Code View Project Workspace Plots Tools Help

Go to file/function Project: (None)

Manchester.R x

Source on Save Run Source

```
1 # Load the library foreign
2 library(foreign)
3
4 # Read in the tutorial stata data set
5 tutorial = read.dta("http://www.bristol.ac.uk/cmm/media/runmlwin/tutorial.dta")
6
7 # Generate a boy dummy variable
8 tutorial$boy <- 1 - tutorial$girl
9
10 # Generate the passexam binary response variable
11 tutorial$passexam <- tutorial$normexam>0
12
13 # Load the library R2MLwin
14 library(R2MLwin)
15
16 # specify the MLwin directory
17 mlwin = "C:/Program Files (x86)/MLwin v2.26/"
18
19 # Declare the levels in the model hierarchy
20 levID = c('school','student')
21
22 # specify the continuous response model
23 formula = "normexam ~ (0 | cons + standlrt + girl) + (2 | cons + standlrt) + (1 | girl + boy)"
24
25 # set the level-1 covariance between the boy and girl residual errors to zero
26 smat = c(2,1)
27
28 # specify estimation by IGLS
29 estoptions = list(EstM=0)
30
31 # Fit the model
32 mymodel = runMLwin(formula, levID, D="Normal", tutorial, estoptions, MLwinPath=mlwin, workdir = tempdir())
33
34
35
36
37:1 (Top Level) R Script
```

Workspace History

Console

```
> # Fit the model
> mymodel = runMLwin(formula, levID, D="Normal", tutorial, estoptions,
+                   MLwinPath=mlwin, workdir = tempdir())
```

worksheet has 50000000 spaces
ECHO 0

Execution completed

MLwin multilevel model (Normal)
Estimation algorithm: IGLS Elapsed time : 0.54s
Number of obs: 4059
Deviance statistic: 9281.4

The model formula:
normexam~(0|cons+standlrt+girl)+(2|cons+standlrt)+(1|girl+boy)
Level 2: school Level 1: student

The fixed part estimates:

	Coef.	Std. Err.	z	Pr(> z)		[95% Conf. Interval]
cons	-0.11153	0.04331	-2.58	0.01001	*	-0.19641 -0.02665
standlrt	0.55294	0.02008	27.54	5.462e-167	***	0.51359 0.59228
girl	0.17528	0.03242	5.41	6.401e-08	***	0.11175 0.23881

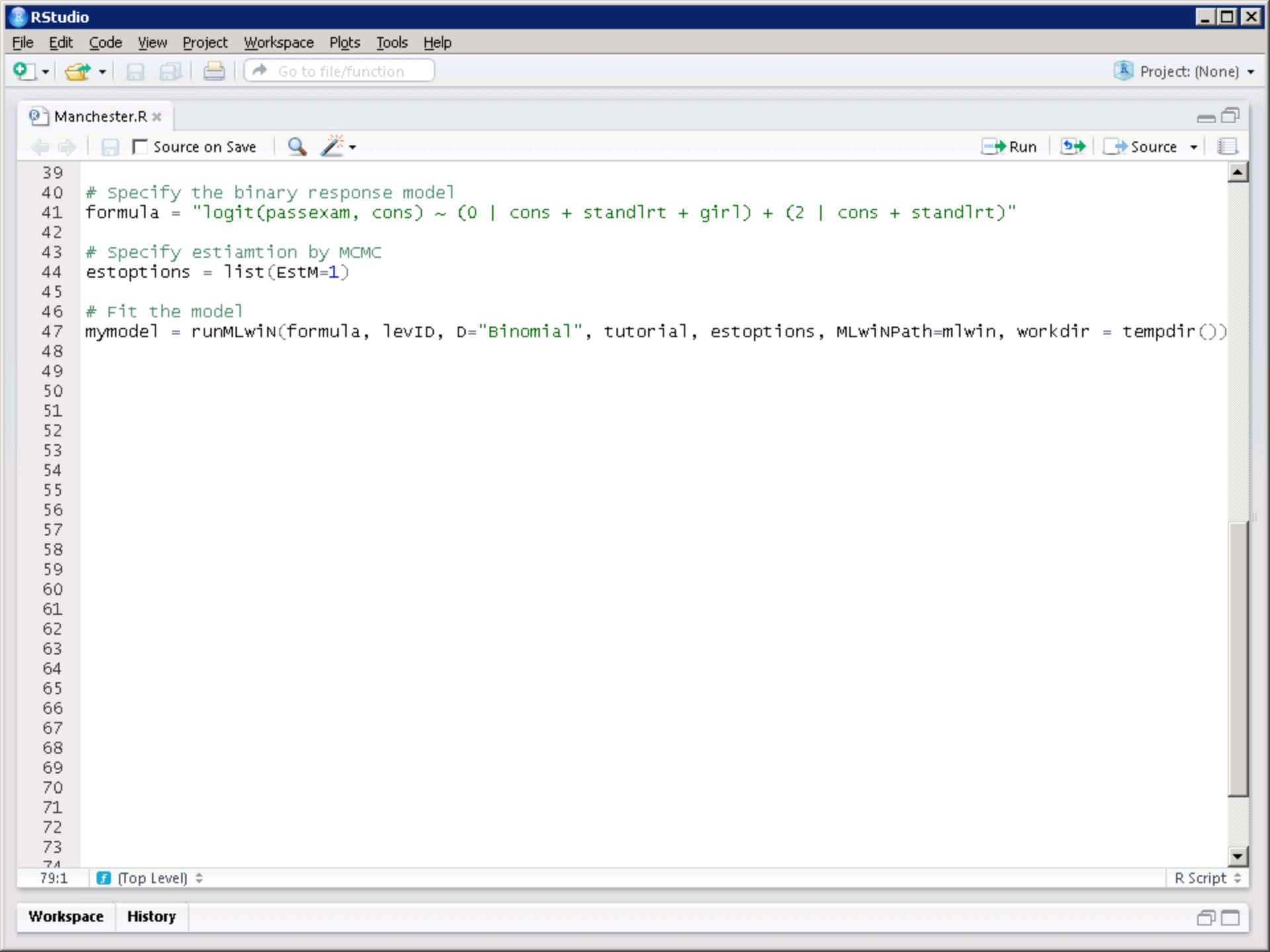
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The random part estimates at the school level:

	Coef.	Std. Err.	[95% Conf. Interval]
var_cons	0.08625	0.01717	0.05259 0.11991
cov_cons_standlrt	0.01905	0.00668	0.00596 0.03214
var_standlrt	0.01489	0.00447	0.00613 0.02365

The random part estimates at the student level:

	Coef.	Std. Err.	[95% Conf. Interval]
var_girl	0.52516	0.01528	0.49521 0.55512
cov_girl_boy	0.00000	0.00000	0.00000 0.00000
var_boy	0.58743	0.02100	0.54628 0.62859



```
39
40 # specify the binary response model
41 formula = "logit(passexam, cons) ~ (0 | cons + standlrt + girl) + (2 | cons + standlrt)"
42
43 # specify estimation by MCMC
44 estoptions = list(EstM=1)
45
46 # Fit the model
47 mymodel = runMLwin(formula, levID, D="Binomial", tutorial, estoptions, MLwinPath=mlwin, workdir = tempdir())
48
49
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71
72
73
74
```

Console

```

Adapting for 1200 iterations (Maximum 5000)
Adapting for 1300 iterations (Maximum 5000)
Adapting for 1400 iterations (Maximum 5000)
Adapting for 1500 iterations (Maximum 5000)
Adapting for 1600 iterations (Maximum 5000)
Adapting finished and took 1700 iterations
Burning in for 0 iterations out of 500
Burning in for 100 iterations out of 500
Burning in for 200 iterations out of 500
Burning in for 300 iterations out of 500
Burning in for 400 iterations out of 500

```

Execution completed

MLwin multilevel model (Binomial)

```

Estimation algorithm: MCMC      Elapsed time : 28.4s
Number of obs: 4059           Number of iter.: 5000      Burn-in: 500

```

Bayesian Deviance Information Criterion (DIC)

Dbar	D(thetabar)	pD	DIC
4234.584	4162.498	72.087	4306.671

The model formula:

```

logit(passexam, cons) ~ (0 | cons + standlrt + girl) + (2 | cons + standlrt)
Level 2: school      Level 1: student

```

The fixed part estimates:

	Coef.	Std. Err.	z	Pr(> z)		[95% Conf. Interval]	ESS
cons	-0.03707	0.10921	-0.34	0.7343		-0.24130 0.19745	82
standlrt	1.35860	0.06101	22.27	7.554e-110	***	1.23754 1.47761	487
girl	0.19848	0.10172	1.95	0.05105	.	-0.00255 0.40455	137

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The random part estimates at the school level:

	Coef.	Std. Err.	[95% Conf. Interval]	ESS
var_cons	0.51187	0.12163	0.31867 0.78817	939
cov_cons_standlrt	0.06201	0.05505	-0.04266 0.17783	159
var_standlrt	0.07720	0.04525	0.01987 0.18716	69



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R2MLwiN: Running MLwiN from within R

R2MLwiN is an R command interface to the MLwiN multilevel modelling software package, allowing users to fit multilevel models using MLwiN from within the R environment. It is designed to be used with versions of MLwiN from v2.25 onwards although some features will work with earlier versions.

Installation

Both [MLwiN](#) and [R](#) are required to use **R2MLwiN**. [MLwiN](#) is [free](#) to UK academics. A fully functional [30-day free version](#) of MLwiN is available to all other users.

To install **R2MLwiN**, type the following at the R command line:

```
install.packages("R2MLwiN", repos="http://cran.r-project.org")
```

Documentation

To see the documentation for **R2MLwiN**, type the following at the R command line:



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Examples using R2MLwiN

MLwiN User Manual

We provide R demos which allow you to replicate all the analysis reported in the [MLwiN MCMC Manual](#) (PDF, 7.4 mb) using R2MLwiN with the package. The table of contents are:

- [01 Introduction to MCMC Estimation and Bayesian Modelling \(R\)](#)
- [02 Single Level Normal Response Modelling \(R\)](#)
- [03 Variance Components Models \(R\)](#)
- [04 Other Features of Variance Components Models \(R\)](#)
- [05 Prior Distributions, Starting Values and Random Number Seeds \(R\)](#)
- [06 Random Slopes Regression Models \(R\)](#)
- [07 Using the WinBUGS Interface in MLwiN \(R\)](#)
- [08 Running a Simulation Study in MLwiN \(R\)](#)
- [09 Modelling Complex Variance at Level 1 / Heteroscedasticity \(R\)](#)
- [10 Modelling Binary Responses \(R\)](#)
- [11 Poisson Response Modelling \(R\)](#)
- [12 Unordered Categorical Responses \(R\)](#)