

A review of random effects models in *MLwiN* (Version 2.0)

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1 Introduction

1.1 Background

MLwiN has been created by the Centre for Multilevel Modelling team based at the Institute of Education together with various colleagues in other centres. The package is a development from *MLn* and its precursor, *ML3* which provided a DOS based system for the specification and analysis of a range of multilevel models. *ML3* was itself developed from an application called *NANOSTAT* which was written by Michael Healy.

The main computation code of *MLwiN* comprises a modified version of the earlier DOS *MLn* package, which is driven by a series of commands and operates in the background behind the Windows front end. Although many users probably never need be aware of the command system, a command window is available for more advanced users and those with macros written for *MLn*. Virtually all model fitting and manipulation can be performed in the front end, although some models still require resort to the command window.

MLwiN was first released in 1997 and Version 2, which offers a number of enhancements, particularly for the fitting of more complex models, was released in beta form in 2003.

1.2 Software and hardware requirements

The recommended hardware and software requirements for running Version 2 (March 2004) include:

A system running MS Windows 95/98/NT/Me/2000/XP
A Pentium-I 166 MHz processor or higher
32 Mb of RAM or more
A Hard disk with at least 20MB of available space

1.3 Data input / output functionality

MLwiN can read data from either ASCII text files or the clipboard. No functionality is provided to read any other file types.

If the data are in a free format ASCII, with items delimited by commas or by one or more spaces or tabs, and if there is the same number of items in each record (terminated by a new line) then the software will read the file using default settings. If the data are in fixed format, with a fixed number of characters for each item, then the package allows the format to be specified using a sequence of formatting codes. In the format specification, users can specify item widths and allow columns to be skipped. Formatted input can be useful if some of the items in a long record do not require to be inputted.

If any data item in a column contains non-numeric characters, then that column will be converted into a categorical variable. If a column contains a mix of data items where some are numbers and others are repeated instances of a single non-numeric text character (e.g. ‘*’) then that pattern will be treated as the code for missing data.

One limitation associated with the input of data from a text file is that the software is unable to read variable names, even if they have been written to the first line of the file. Whilst this is not a problem for a small dataset, it is a serious limitation in cases where there are many variables, as each name would need to be re-entered. To circumvent this limitation, if data is held in another package such as EXCEL or SPSS then it may be pasted into *MLwiN* via the windows clipboard. The software provides a useful preview window that allows the user to check that the structure of the data has been correctly interpreted, and also allows you to specify the column within which to place each variable. Usefully, importing data via this route also allows you to paste variable names if they are held on the clipboard. Hence this will be the preferable methodology for the majority of users.

Once inside the software, *MLwiN* contains a number of advanced features for arranging the data into the forms required for fitting various multilevel structures. However, the facilities for basic data editing (viewing values, recoding etc.) are somewhat limited compared to packages such as EXCEL. Therefore most users will find it preferable to clean their data in another package before importing into *MLwiN*.

Data can be output from the package to a text file. There are no facilities to copy values to the clipboard. Whilst the output facilities are limited, there are relatively few situations where a user would wish to write significant amounts of data from *MLwiN* into a different package.

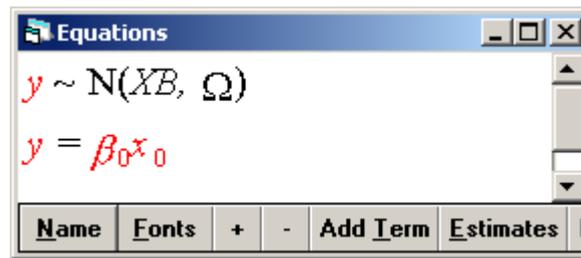
Once a model has been imported into *MLwiN* it can be saved using the packages own file form, a .ws file. This format has the significant advantage of saving all of the model structure, along with the most recent parameter estimates, in the same file as the data. This is particularly useful for more complex models as it means that they only need to be set up once. Regular saving this way also has the advantage that work can quickly be regained after the occasional software crash.

4. Interface features: data manipulation, commands, menus

Version 2 of the software sees the continued development of the sophisticated user interface. Virtually all of the functions of the package are access from the ten menus provided on the main title bar.

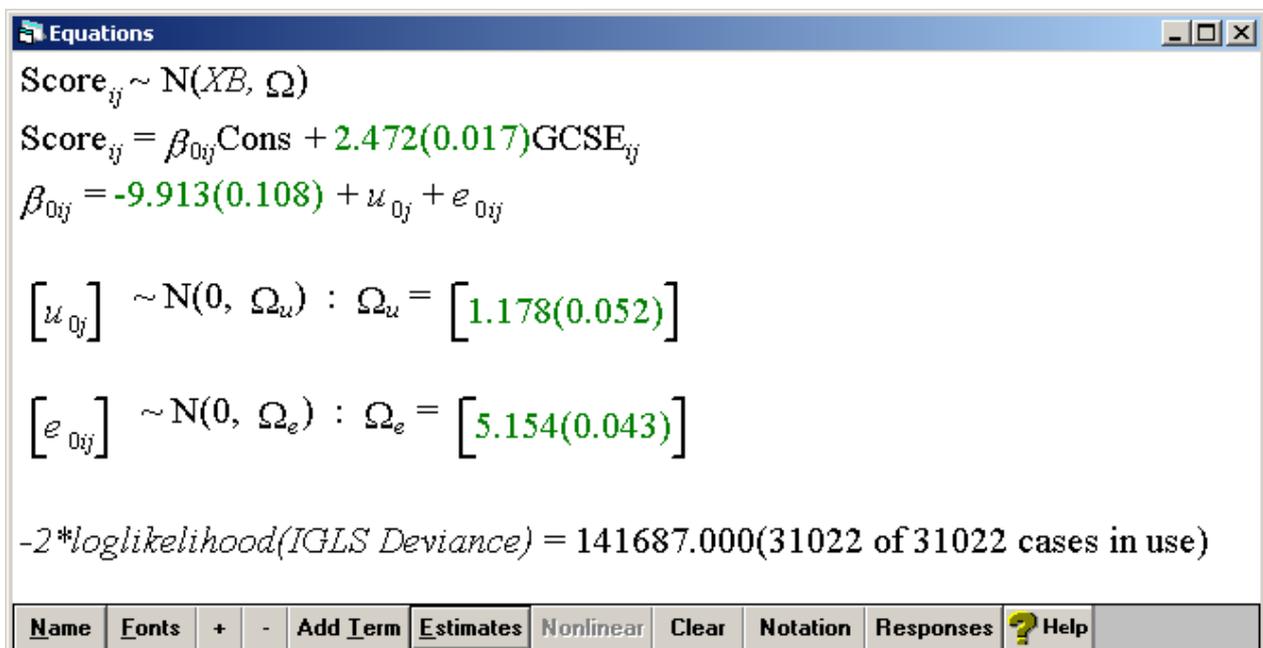


The help system is one of the most comprehensive of any Windows package, and most windows provide the option for context sensitive help. The equations window will be the centre of most analyses undertaken using the package, and the producers of other statistical software packages could learn a lot from this innovative feature. Rather than specifying the model to be fitted using drop down menus and variables copied into boxes, the equations window allow the model to be fitted to be built graphically on screen. When first opened, the window displays a null model



This default window highlights the notation used by the package. In this case the default model is one where the outcome variable, y , is assumed to be normally distributed with a mean of XB and a variance described by the parameter Ω . The null model contains just one, as yet unspecified, variable x_0 which has a slope coefficient β_0 . Clicking on the N will allow different specifications (Binomial, Poisson, negative Binomial, Normal, Multinomial) to be defined. Parameters shown in red in the equations window are still to be defined. So, clicking on y allows the outcome variable to be specified, along with the number of levels in the model, and the level identifier codes. Clicking on the undefined parameter x_0 will allow the first explanatory variable, usually the intercept, to be defined. The window can then be used to add or delete variables from the model, and change the model structure.

One of the most innovative features of the Equations window is that it not only allows models to be set up, but also displays the results using the standard model notation. Although this has the potential of being daunting to newcomers, particularly those without previous modelling experience, it quickly becomes intuitive and helps avoid those “What does that number mean?” situations as the specified model and associated parameters are integrated. As an example, the results from a three level model fitted to the CHEM97 dataset, discussed more later, are shown below.



In the above example, the 1997 point score on A-level chemistry (Score) is being modelled in a two level structure with i pupils nested within j schools. The intercept is -9.913 (standard error 0.017) and a 1 mark increase in GCSE score is associated with a predicted 2.472 (standard error

0.017) mark increase in A-level score. The residual variance at the school level (described by the term u_{0j}) is 1.178 (standard error 0.052) and at the pupil level (described by the term e_{oij}) 5.154 (standard error 0.043). The deviance statistic for this model is 141687.

In addition to the equations window, *MLwiN* contains menus to select different model diagnostics, estimation methods, and data manipulation functions. It can also calculate basic statistics such as correlation coefficients and averages, although the output from this function uses the command line interface window which is not nearly as eloquent as the equations window functionality.

Although *MLwiN* does not have the functionality to produce the kind of publication quality polished graphs that can be generated in packages like Excel, it does have some advanced graphical capabilities. Particularly useful are the selection and linkage features; data points

Table 1 Multilevel models that can be fitted in MLwiN

Data / model type	Estimation procedures	Limitation on levels in data	Allowing covariates	Allowing random slopes	Weighting	Fitting variance function (any level)	Other comments/ limitations
Normal response	IGLS, RIGLS, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	
Binary/Binomial	PQL, MQL, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	No extra binomial in MCMC
Poisson	PQL, MQL, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	No extra Poisson in MCMC
Negative Binomial	PQL, MQL, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	
Repeated measures	IGLS, RIGLS, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	
Nominal multinomial	PQL, MQL, MCMC	None	Yes	Yes	No	No	
Ordered multinomial	PQL, MQL, MCMC	None	Yes	Yes	No	No	
Cross-classified	IGLS, RIGLS, PQL, MQL, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	Available for Normal, Binary and count data
Multiple membership	IGLS, RIGLS, MCMC, Bootstrap	None	Yes	Yes	Yes	Yes	
Survival	IGLS, RIGLS, PQL, MQL, MCMC	None	Yes	Yes	Yes (for Cox model only)	Yes	Uses additional macros
Time series	IGLS, RIGLS, PQL, MQL, MCMC	None	Yes	Yes	No	Yes	Uses additional macros
Multivariate Normal	IGLS, RIGLS, PQL, MQL, MCMC, Bootstrap	None	Yes	Yes	Yes	No	Available for Normal, Binary and count data
Multiple mixed responses	IGLS, RIGLS, MCMC, Bootstrap	None	Yes	Yes	No	No	Some combinations not possible
Nonlinear	Not available						
Structural Equation models	Not available						

selected in one graph using point and click functionality can be highlighted in other graphs, excluded from the currently fitted model, or added as dummy variables. This is particularly useful when working on model diagnostics. Another nice feature is that all graphs are dynamic so if the data behind one changes, perhaps as a result of modifying a model, then the graph will automatically update.

2. Standard modelling tools for multilevel analysis

2.1 A brief checklist of facilities for multilevel modelling in *MLwiN*

Table 1 provides an overview of the facilities for fitting multilevel models in *MLwiN*. The flexibility of the software is highlighted by the wide range of models that can be specified.

2.2 Tools for statistical inference and model diagnostics

A range of diagnostic and inferential tools are available in *MLwiN* as outlined in Table 2.

Table 2 *MLwiN* tools for inference and diagnostics

Models that can be fitted	Tests for overall goodness of fit	Inference on fixed effects,	Inference on random effects	Diagnostics
Normal response	Deviance	SE, Wald test	Variance, SE, Wald test	Residual plots, standardised residuals, plots of random coefficients, leverage values, influence statistics, deletion residuals. For MCMC: PACF plots, MCSE, Raftery-Lewis diagnostic, Brooks-Draper diagnostic.
Generalised Linear model	Not available	SE, Wald test	Variance, SE, Wald test	As above

Parameter estimates, standard errors and, in the case of normal models, deviance statistics are all given in the equations window. P values are not provided by default but can be calculated using the intervals and tests option found under the Model menu option for Wald test and using the tail areas option under the Basic Statistics menu for the probability of Normal score and Chi-Squared statistics. A comprehensive graphical display of model diagnostics, including residuals, leverage, and influence statistics is available via the residuals window. When Markov Chain Monte Carlo (MCMC) procedures are being used, a series of MCMC diagnostics are available for each parameter by clicking on that parameter in the Equations window.

3. Model specifications -- Basic models

The models in the following sections were fitted using *MLwiN* 2.0 on a Viglen PC with an 833Mhz Intel Pentium 3 processor and 256 Mb RAM running Windows NT4. Models are specified in the tables below in symbolics.

3.1 Two-level Normal models

The first set of data examined (EXAM) consists of 4,059 students from 65 schools. The example dataset was selected from a very much larger set of examination results from six inner London Education Authorities. The aim of the original analysis was to establish whether some schools were more 'effective' than others in promoting students' learning and development, taking account of variations in the characteristics of students when they started Secondary school. The columns are:

- SCHOOL: School ID
- PUPIL: Student ID
- NORMEXAM: Normalised exam score as outcome variable
- CONS: Constant vector of 1
- STANDLRT: Standardised LR test score as intake variable
- SEX: Student gender (0 = boys, 1 = girls)
- SCHGEND: School gender (1 = mixed school, 2 = boys school, 3 = girls school)
- AVEINT: School average of intake score
- BANDS: Band of school means on intake score (1 = bottom 25%, 2 = mid 50%, 3 = top 25%)
- BANDP: Band of students intake score (1 = bottom 25%, 2 = mid 50%, 3 = top 25%)

Table 3 *MLwiN* specifications for 3-level Normal models

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Variance components without covariates	Constant (β_0)	School σ^2_{u0} , Pupil σ^2_{e0}	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_0 = -0.013 (0.054)$ $\sigma^2_{u0} = 0.169 (0.032)$ $\sigma^2_{e0} = 0.848 (0.019)$	Less than 1
Variance component with covariates 'standlrt', 'gender' and 'schgend'	β_0 , Standlrt (β_1), Gender 0/1 (β_2), Schgend 1/2/3 (β_{31} , β_{32} , β_{33})	σ^2_{u0} , σ^2_{e0}	As above but include new explanatory variables	$\beta_0 = -0.168 (0.054)$ $\beta_1 = 0.560 (0.012)$ $\beta_2 = 0.167 (0.034)$ $\beta_{32} = 0.178 (0.111)$ $\beta_{33} = 0.159 (0.087)$ $\sigma^2_{u0} = 0.081 (0.016)$ $\sigma^2_{e0} = 0.562 (0.013)$	Less than 1
Random slopes on 'standlrt'	β_0 , β_1 , β_2 , β_{31} , β_{32} , β_{33}	σ^2_{u0} , School slope σ^2_{u1} , School cov σ_{u01} , σ^2_{e0}	As above, but indicate that 'standlrt' also to be fitted at level 2	$\beta_0 = -0.189 (0.051)$ $\beta_1 = 0.554 (0.020)$ $\beta_2 = 0.180 (0.099)$ $\beta_{32} = 0.175 (0.079)$ $\beta_{33} = 0.168 (0.034)$ $\sigma^2_{u0} = 0.080 (0.016)$ $\sigma^2_{u1} = 0.015 (0.004)$ $\sigma_{u01} = 0.020 (0.006)$ $\sigma^2_{e0} = 0.550 (0.012)$	Approx 1
Level 1 variances by 'gender'	β_0 , β_1 , β_2 , β_{31} , β_{32} , β_{33}	σ^2_{u0} , σ^2_{u1} , σ_{u01} Variance girls σ^2_{e0} , Variance boys σ^2_{e1}	As above, but indicate that 'gender' to be fitted at level 2	$\beta_0 = -0.189 (0.052)$ $\beta_1 = 0.554 (0.020)$ $\beta_2 = 0.168 (0.034)$ $\beta_{32} = 0.180 (0.100)$ $\beta_{33} = 0.175 (0.078)$ $\sigma^2_{u0} = 0.080 (0.016)$ $\sigma^2_{u1} = 0.015 (0.004)$ $\sigma_{u01} = 0.020 (0.007)$ $\sigma^2_{e0} = 0.588 (0.021)$ $\sigma^2_{e1} = -0.062 (0.026)$	Approx 1
Level 1 variance as function of 'standlrt'	β_0 , β_1 , β_2 , β_{31} , β_{32} , β_{33}	σ^2_{u0} , σ^2_{u1} , σ_{u01} , σ^2_{e0} , σ^2_{e2} , σ_{e02}	As above, but indicate that 'standlrt' to be fitted at level 2	$\beta_0 = -0.189 (0.051)$ $\beta_1 = 0.556 (0.020)$ $\beta_2 = 0.169 (0.034)$ $\beta_{32} = 0.177 (0.099)$ $\beta_{33} = 0.175 (0.079)$ $\sigma^2_{u0} = 0.080 (0.016)$ $\sigma^2_{u1} = 0.014 (0.004)$ $\sigma_{u01} = 0.021 (0.006)$ $\sigma^2_{e0} = 0.550 (0.015)$ $\sigma^2_{e2} = 0.001 (0.009)$ $\sigma_{e02} = -0.015 (0.006)$	Approx 2

3.2 Three-level Normal models

This example data is very large, and is thus useful to test the efficiency of the estimation algorithm. It contains information on 31,022 individuals in about 2,280 schools. This file is from an A/AS-level data analysis project covering the period 1998 to 2001. It consists of 7 fields in the following order:

- LEA: ID for Local Education Authorities (LEA)
- SCHOOL: ID for schools
- PUPIL: ID for individuals
- POINTS: Point score on A-level Chemistry in 1997
- GENDER: Gender (M=0; F=1)
- AGE: Age in month, centred at 222 months or 18.5 years
- GCSE: Average GCSE scores of individual's

Table 4 *MLwiN* specifications for 3-level Normal models

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Variance component without covariates	Constant β_0	LEA σ^2_{v0} , School σ^2_{u0} , Pupil σ^2_{e0} ,	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_0 = 5.319 (0.058)$ $\sigma^2_{v0} = 0.149 (0.048)$ $\sigma^2_{u0} = 2.749 (0.114)$ $\sigma^2_{e0} = 8.516 (0.071)$	3
Variance component with covariates 'GCSE' and 'gender'	β_0 , GCSE (β_1) Gender 0/1 (β_2)	σ^2_{v0} , σ^2_{u0} , σ^2_{e0}	As above but include new explanatory variables.	$\beta_0 = -10.104 (0.108)$ $\beta_1 = 2.560 (0.017)$ $\beta_2 = -0.741 (0.030)$ $\sigma^2_{v0} = 0.019 (0.013)$ $\sigma^2_{u0} = 1.132 (0.051)$ $\sigma^2_{e0} = 5.058 (0.042)$	3
Random slopes on 'GCSE'	β_0 , β_1 , β_2	σ^2_{v0} , σ^2_{u0} , School slope σ^2_{u1} , School cov σ_{u01} , σ^2_{e0}	As above but indicate GCSE also to be fitted at level 2	$\beta_0 = -10.590 (0.132)$ $\beta_1 = 2.635 (0.020)$ $\beta_2 = -0.745 (0.030)$ $\sigma^2_{v0} = 0.003 (0.009)$ $\sigma^2_{u0} = 10.475 (1.005)$ $\sigma^2_{u1} = 0.170 (0.022)$ $\sigma_{u01} = -1.280 (0.147)$ $\sigma^2_{e0} = 4.955 (0.042)$	7
Level 1 variances by 'gender'	β_0 , β_1 , β_2	σ^2_{v0} , σ^2_{u0} , σ^2_{u1} , σ_{u01} , σ^2_{e0} , σ^2_{e1}	As above but indicate gender also to be fitted at level 1	$\beta_0 = -10.591 (0.132)$ $\beta_1 = 2.635 (0.020)$ $\beta_2 = -0.745 (0.030)$ $\sigma^2_{v0} = 0.003 (0.009)$ $\sigma^2_{u0} = 10.498 (1.007)$ $\sigma^2_{u1} = 0.170 (0.022)$ $\sigma_{u01} = -1.284 (0.148)$ $\sigma^2_{e0} = 4.955 (0.042)$ $\sigma^2_{e1} = 0.000 (0.000)$	9
Level 1 variance as function of 'GCSE'	β_0 , β_1 , β_2	σ^2_{v0} , σ^2_{u0} , σ^2_{u1} , σ_{u01} , σ^2_{e0} , σ^2_{e1} , σ_{e01}	As above but indicate GCSE to be fitted at level 1	Model failed to converge	

3.3 Two-level models for binary data

These data come from the 1988 Bangladesh Fertility Survey. The dataset consists of a sub-sample of 1934 women grouped in 60 districts. The variables are defined as follows:

- WOMAN: identifying code for each woman
- DISTRICT: identifying code for each district
- USE: Contraceptive use status at time of survey: response variable
1 = using contraception, 0 = not using contraception
- CHILDREN: Number of living children at time of survey
1 = None
2 = 1
3 = 2
4 = 3 or more
- AGE: Age of woman at time of survey (in years), centred at mean
- URBAN: Type of region of residence
1 = Urban
0 = Rural
- CONS: vector of 1s

Table 5 *MLwiN* specifications for 2-level logistic model (2nd order PQL estimation)

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Variance component with all covariates -- logistic link, MQL	Constant β_0 , Children 1/2/3+ (β_{11} , β_{12} , β_{13}), Age (β_2), Urban (β_3)	District σ^2_{u0}	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_0 = -1.693 (0.129)$ $\beta_{11} = 1.090 (0.130)$ $\beta_{12} = 1.421 (0.143)$ $\beta_{13} = 1.350 (0.147)$ $\beta_2 = -0.021 (0.006)$ $\beta_3 = 0.779 (0.100)$ $\sigma^2_{u0} = 0.245 (0.067)$	Less than 1
Random effect on the covariate URBAN -- logistic link, MQL	$\beta_0, \beta_{11}, \beta_{12}, \beta_{13}, \beta_2, \beta_3$	σ^2_{u0} , District urban σ^2_{u1} , District cov σ_{u01}	As above but indicator URBAN also fitted at level 2	$\beta_0 = -1.706 (0.137)$ $\beta_{11} = 1.097 (0.131)$ $\beta_{12} = 1.425 (0.144)$ $\beta_{13} = 1.359 (0.148)$ $\beta_2 = -0.021 (0.006)$ $\beta_3 = 0.813 (0.135)$ $\sigma^2_{u0} = 0.355 (0.174)$ $\sigma^2_{u1} = 0.343 (0.094)$ $\sigma_{u01} = -0.221 (0.107)$	Approx 1
Random effect on the covariate URBAN -- probit link, MQL	$\beta_0, \beta_{11}, \beta_{12}, \beta_{13}, \beta_2, \beta_3$	$\sigma^2_{u0}, \sigma^2_{u1}, \sigma_{u01}$	As above but indicate Probit link	$\beta_0 = -1.043 (0.081)$ $\beta_{11} = 0.666 (0.078)$ $\beta_{12} = 0.869 (0.086)$ $\beta_{13} = 0.829 (0.088)$ $\beta_2 = -0.013 (0.004)$ $\beta_3 = 0.503 (0.083)$ $\sigma^2_{u0} = 0.136 (0.066)$ $\sigma^2_{u1} = 0.128 (0.035)$ $\sigma_{u01} = -0.085 (0.040)$	Approx 1
Random effect on the covariate URBAN – log-log link, MQL	$\beta_0, \beta_{11}, \beta_{12}, \beta_{13}, \beta_2, \beta_3$	$\sigma^2_{u0}, \sigma^2_{u1}, \sigma_{u01}$	As above but indicate loglog link	$\beta_0 = -1.694 (0.110)$ $\beta_{11} = 0.834 (0.102)$ $\beta_{12} = 1.085 (0.109)$ $\beta_{13} = 1.058 (0.115)$ $\beta_2 = -0.015 (0.005)$ $\beta_3 = 0.616 (0.099)$ $\sigma^2_{u0} = 0.204 (0.095)$ $\sigma^2_{u1} = 0.213 (0.059)$ $\sigma_{u01} = -0.146 (0.064)$	Approx 1

3.4 Three/two-level models for count data

This dataset comes from the study of Malignant Melanoma Mortality in the European Community associated with the impact of UV radiation exposure. Seven fields are included in the set. Three-level structure presents county nested within region nested within nation. The variables are defined as follows:

- NATION: (1=Belgium, 2 = W.Germany, 3 = Denmark, 4 = France, 5 = UK, 6 = Ireland, 7 = Luxembourg, 8 = Netherlands, 9 = Italy)
- REGION: Region ID
- COUNTY: County ID
- DEATHS: Number of male deaths due to MM during 1971~ 1980
- EXPECTED: Number of expected deaths
- CONS: Constant vector of 1
- UVB: Measure of the UVB dose reaching the earth's surface in each county. Centred.

Table 6 *MLwiN* specifications for multilevel Poisson model (fitted using 2nd order PQL estimation)

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
3-level variance components with the covariate UVB index. Log of expected deaths fitted as offset.	Constant β_0 , UVB (β_1).	Nation σ^2_{v0} , Region σ^2_{u0}	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_0 = -0.081 (0.133)$ $\beta_1 = -0.028 (0.011)$ $\sigma^2_{v0} = 0.136 (0.072)$ $\sigma^2_{u0} = 0.048 (0.011)$	Approx 1
2-level variance component with fixed effects on nations. Log of expected deaths fitted as offset.	β_0, β_1 , W Germ β_{21} , Denmark β_{22} , France β_{23} , UK β_{24} , Ireland β_{25} , Luxe β_{26} , Netherlands β_{27} , Italy β_{28}	σ^2_{u0}	Set model as 2 level. Defined NATION as a categorical variable. Added NATION as a fixed effect.	$\beta_0 = -0.157 (0.134)$ $\beta_1 = 0.027 (0.011)$ $\beta_{21} = -0.590 (0.146)$ $\beta_{22} = 0.780 (0.183)$ $\beta_{23} = -0.394 (0.148)$ $\beta_{24} = -0.016 (0.148)$ $\beta_{25} = 0.093 (0.172)$ $\beta_{26} = -0.504 (0.215)$ $\beta_{27} = 0.103 (0.322)$ $\beta_{28} = 0.159 (0.173)$ $\sigma^2_{u0} = 0.042 (0.009)$	Approx 1

3.5 Growth type models for repeated measures data

In this dataset measurements of the height of 26 boys were taken on 9 occasions between the ages of 11 and 13 years. The measurements are approximately 0.25 year apart. There are six fields in the data:

- PERSON: Individual ID
- AGE: Age centred at 12 years
- HEIGHT: Height in cm
- OCC: Occasion number
- SEASON: Season in decimal year
- CONS: Constant term

Table 7 *MLwiN* specifications for repeated measures 'growth' model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Polynomial growth model (cubic term) with random coefficient (quadratic) without time series	Constant β_0 , Age (β_1), Age ² (β_2), Age ³ (β_3), Age ⁴ (β_4)	Person σ^2_{u0} , Age (σ^2_{u1}), Age ² (σ^2_{u2}), Covariances; σ_{u10} , σ_{u20} , σ_{u21} Occasion σ^2_{e0}	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_0 = 148.971 (1.541)$ $\beta_1 = 6.165 (0.351)$ $\beta_2 = 1.090 (0.349)$ $\beta_3 = 0.468 (0.162)$ $\beta_4 = -0.340 (0.300)$ $\sigma^2_{u0} = 61.567 (17.083)$ $\sigma^2_{u1} = 2.762 (0.783)$ $\sigma^2_{u2} = 0.630 (0.225)$ $\sigma_{u10} = 7.994 (3.022)$ $\sigma_{u20} = 1.364 (1.406)$ $\sigma_{u21} = 0.875 (0.342)$ $\sigma^2_{e0} = 0.217 (0.025)$	Less than 1
The above model with time series	$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$	$\sigma^2_{u0}, \sigma^2_{u1}, \sigma^2_{u2},$ $\sigma_{u10}, \sigma_{u20}, \sigma_{u21},$ σ^2_{e0}	Set up and ran time series macros from the command line. Time series options not available from the menus in release 2	$\beta_0 = 149.000 (1.539)$ $\beta_2 = 1.253 (0.377)$ $\beta_3 = 0.433 (0.174)$ $\beta_4 = -0.495 (0.319)$ $\sigma^2_{u0} = 61.48 (17.070)$ $\sigma^2_{u1} = 2.681 (0.767)$ $\sigma^2_{u2} = 0.564 (0.300)$ $\sigma_{u10} = 7.189 (2.248)$ $\sigma_{u20} = 1.483 (1.404)$ $\sigma_{u21} = 0.854 (0.337)$ $\sigma^2_{e0} = 0.250 (0.045)$ TS parameter = 6.185 (0.3525)	Approx 1

3.6 Multinomial model for ordered or unordered response

The data come from British Social Attitudes (BSA) Survey started in 1983. The eligible persons were all adults aged 18 or over living in private households in Britain. The data refer to surveys carried out in 1983, 1984, 1985 and 1986. There were seven dichotomous items asking whether the respondent supported or opposed a woman's right to have an abortion under different circumstances each year. Finally there were 410 respondents who responded to all four years' interviews in 54 districts. The data consist of completed results of 264 respondents out of 410. There are 1056 records from the joining of four years' data. The fields are:

- ID: District ID
- RESPOND: Respondent code (within district)
- YEAR: Year code (1=1983, 2=1984, 3=1985, 4=1986)
- ANSWERS: Number of positive answers up to seven questions (1=yes for one item or none, 2=yes for two items, ..., 7=yes for seven items)
- PARTY: Party chosen (1=conservative, 2=labour, 3=Lib/SDP/Alliance, 4=others, 5=none)
- SCLASS: Self assessed social class (1=middle, 2 =upper working, 3=lower working)
- GENDER: Gender (1=male, 2=female)
- AGE: Age in years
- RELIGION: Religion (1=Roman catholic, 2=Protestant/Church of England, 3=others, 4=none)
- ID: Individual ID (unique)
- CONS: Constant term

Table 8 *MLwiN* specifications for multinomial response model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Multinomial unordered variance components response model.	Constant (T (Less than or equal to 1 item) (β_{01})... Constant 7+ items (β_{07});	Level 2 (respondent) V_{0k}	Use equations window to specify outcome, variables, and multilevel structure.	$\beta_{02}= 0.518 (0.143)$, $\beta_{03} = 2.081 (0.073)$, $\beta_{04} = 1.411 (0.095)$ $\beta_{05}= 1.387 (0.096)$, $\beta_{06} = 1.509 (0.091)$, $\beta_{07} = 2.391 (0.096)$, $v_{0k} = 1.363 (0.187)$	Approx 30 seconds
Multinomial ordered variance components response model.	$\beta_{01} - \beta_{07}$	V_{6k}	Use equations window to switch to ordered response	$\beta_{01}=3.641 (0.194)$, $\beta_{02} = 2.515 (0.137)$, $\beta_{03} = -0.802 (0.098)$ $\beta_{04}=0.282 (0.095)$, $\beta_{05} = -0.190 (0.095)$, $\beta_{06} = -0.753 (0.098)$, $v_{0k} = 10.936 (0.652)$	Approx 30 seconds
Multinomial unordered response model with voting covariates.	$\beta_{01} - \beta_{07}$, Labour (β_{12})... (β_{17}), LibDem (β_{22})... (β_{27}), Others (β_{32})... (β_{37}) None (β_{42})... (β_{47})	Level 2 and 3 variances and covariances (parameters not given)		$\beta_{02}=0.612(0.279)$, $\beta_{03} = 2.096 (0.160)$, $\beta_{04} = 1.351 (0.174)$ $\beta_{05}=1.385(0.165)$, $\beta_{06} = 1.600 (0.165)$, $\beta_{07} = 2.4 (0.157)$, $\beta_{12} = -0.296 (0.417)$, $\beta_{13} = 0.056, (0.226)$, $\beta_{14} = 0.195 (0.242)$, $\beta_{15} = 0.259 (0.227)$, $\beta_{16} = -0.117 (0.243)$, $\beta_{17} = -0.045 (0.221)$, $\beta_{22} = 0.272 (0.428)$, $\beta_{23} = 0.162 (0.250)$, $\beta_{24} = 0.173 (0.283)$, $\beta_{25} = -0.089 (0.291)$, $\beta_{26} = 0.222 (0.264)$, $\beta_{27} = 0.118 (0.241)$, $\beta_{32} = 0.648 (0.705)$, $\beta_{33} = 0.142 (0.462)$, $\beta_{34} = 0.414 (0.499)$, $\beta_{35} = -0.732 (0.757)$, $\beta_{36} = -0.885 (0.752)$, $\beta_{37} = 0.220 (0.432)$ $\beta_{42} = -68.19 (217.0)$, $\beta_{43} = -1.173 (0.579)$, $\beta_{44} = -0.758 (0.629)$, $\beta_{45} = -0.874 (0.639)$, $\beta_{46} = -1.519 (0.773)$, $\beta_{47} = -1.009 (0.513)$	Approx 10 mins
Multinomial ordered response model.	$\beta_{01} \dots \beta_{07}$, $\beta_{12} \dots \beta_{17}$, $\beta_{22} \dots \beta_{27}$, $\beta_{32} \dots \beta_{37}$, $\beta_{42} \dots \beta_{47}$	Level 2 and 3 variances and covariances (22 parameters; not given)	As above	Model failed to converge	



3.7 Cross classified model

The data are on 3,435 children who attended 148 primary schools and 19 secondary schools in Scotland. The fields in the data set are:

- VRQ: A verbal reasoning score from tests pupils took when they entered secondary school.
- ATTAIN: Attainment score of pupils at age 16.
- PID: Primary school identifying code.
- SEX: Pupil's gender (boy=0, girl=1).
- SC: Pupil's social class scale (continuous score from low to high social class).
- SID: Secondary school identifying code.
- CONS: Vector of 1's.

Table 9 *MLwiN* specifications for cross classified model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Cross classified (primary x secondary school) variance components model	Constant β_0 ,	Primary school variance (σ^2_{u0}), Secondary school variance (σ^2_{v0}), Between individual variance (σ^2_{e0})	Use equations windows to set up model. Use command interface to set up cross classification (Also available from menus when using MCMC estimation).	$\beta_0 = 5.504 (0.175)$ $\sigma^2_{u0} = 1.124 (0.198)$ $\sigma^2_{v0} = 0.348 (0.162)$ $\sigma^2_{e0} = 8.112 (0.200)$	5 seconds
The above model with gender added as a covariate	β_0 , Gender (β_1)	$\sigma^2_{u0}, \sigma^2_{v0}, \sigma^2_{e0}$	As above and added gender in equations window	$\beta_0 = 5.257 (0.181)$ $\beta_1 = 0.499 (0.098)$ $\sigma^2_{u0} = 1.104 (0.196)$ $\sigma^2_{v1} = 0.346 (0.162)$ $\sigma^2_{e0} = 8.053 (0.199)$	5 seconds

3.8 Multivariate response model

The data consists of scores on two components of a science examination taken in 1989 by 1905 students in 73 schools in England. The examination is the General Certificate of Secondary Education (GCSE) taken at the end of compulsory schooling. The first component is a traditional written question paper (out of 160) and the second is a coursework score (out of 108). The data consists of:

- SCHOOL: School identification
- STUDENT: Student identification
- FEMALE: 1 = female, 0 = male
- AGE: Age in months
- WRITTEN: Score on the written component
- CSEWORK: Score on the coursework component
- CONS: Vector of 1's

Two models have been fitted to this dataset. In the first both written examination and coursework scores are treated as continuous. However, *MLwiN* also allows mixed response multivariate models to be fitted. To illustrate this, in the second model, the written examination scores have been converted to a binary 'high' 'low' indicator where values over 80 are coded '1' and all other

values are coded '0'. That the model has then been refitted with the variable specified as a binary response.

Table 10 *MLwiN* specifications for multivariate response model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Two level (pupil, response) variance components model	Constant, written β_0 , Constant coursework β_1	Pupil level variance written (σ^2_{u0}), variance coursework (σ^2_{u1}), covariance (σ_{u10}),	Use equations windows to set up model. Use 'Responses' option to specify multivariate response.	$\beta_0 = 46.802(0.320)$ $\beta_1 = 73.364 (0.388)$ $\sigma^2_{u0} = 178.705 (6.108)$ $\sigma^2_{u1} = 265.436 (9.017)$ $\sigma_{u10} = 102.301 (5.918)$	3 seconds
The above variable but with 'written' coded as 'high' (>80) and 'low' <=80	β_0, β_1	$\sigma^2_{u0}, \sigma^2_{u1}, \rho\sigma_{u0g}(\pi_{2j})^{0.5}$	As above but specified 'written' as binomial with logit link	$\beta_0 = -4.948 (0.290)$ $\beta_1 = 73.440 (0.388)$ $\sigma^2_{u1} = 266.303 (9.068)$ $\rho\sigma_{u0g}(\pi_{2j})^{0.5} = 1.183 (0.417)$	5 seconds

3.9 Multiple Membership Model

Multiple membership models are used in situations where level 1 units belong to two or more higher level units. In a longitudinal study of school students, for example, many will change their schools and thus belong to more than one school during the study. When modelling such data, a student receives a weighted combination of residuals from all the schools to which the student belongs.

The example below uses the same dataset described in Section 3.7 but has additional schools simulated so that 10% of the sample change school to a new, randomly selected, school once during the period of study. Those pupils who attended two schools are assumed to have spent the same period of time at each

Table 11 *MLwiN* specifications for multiple membership model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Multiple membership 2 level model of pupils nested within secondary schools	Constant β_0 ,	Secondary school variance (σ^2_{u0}), between individual variance (σ^2_{e0})	Use equations window to set up basic model. Use command window to set up multiple membership element	$\beta_0 = 5.562 (0.109)$ $\sigma^2_{u0} = 0.825 (0.295)$ $\sigma^2_{e0} = 8.075 (0.201)$	4 seconds
The above model with gender added as a covariate	β_0 , Gender β_1	$\sigma^2_{u0}, \sigma^2_{e0}$	As above and added gender in equations window	$\beta_0 = 5.316 (0.119)$ $\beta_1 = 0.499 (0.098)$ $\sigma^2_{u0} = 0.801 (0.291)$ $\sigma^2_{e0} = 8.017 (0.200)$	4 seconds

3.10 Survival Model

The term survival data refers to the length of time, t , that corresponds to the time period from a well-defined start time t_0 until the occurrence of some particular event or end-point. It is a common outcome measure in medical studies for relating treatment effects to the survival time of

patients. In these cases, the typical start time is when the patient first received the treatment, and the end point is when the patient died or was lost to follow-up. *MLwiN* can fit multilevel log-duration model or parametric survival models with the macro ‘SURVIVAL’ and fit multilevel proportional hazard models in the standard equation window after using the command language to prepare the data.

The example dataset consists of the lifetimes in years of Malmö residents at the time of the 2000 Swedish Census. They are closed cohorts of people 65 ~69 years old in 1970 and followed up over 30 years. The dataset includes information on mortality and other explanatory variables. The age of an individual who was still alive at the 2000 Census or who was lost after the 1970 Census is treated as a censored time. The individuals are nested within 11,038 households, and households are nested within 21 parishes in the city.

The variables are:

- PARISH: Level 3 ID,
- HOUSEHOLD: Level 2 ID,
- INDIVIDUAL: Level 1 ID,
- AGE1970: Age of individual in 1980,
- MALE: 1 = Male, 0 = Female,
- DEATH: 1 = Died, 0 = otherwise,
- AGE2000: Age last seen,
- FAMILYSIZE: Total members in household,
- FAMILYINCOME: Disposable family income, 100SEK,
- LOG(T): Natural log of ‘AGE2000’,
- CONS: Constant vector of 1’s
- CENSORED: Censored flag censored = 1

Table 12 *MLwiN* specifications for log-duration model

<i>Model</i>	<i>Fixed parameters</i>	<i>Random effects</i>	<i>Steps to set up model</i>	<i>Estimates (SE)</i>	<i>Seconds to convergence</i>
Single level log duration model of survival	Constant β_0 , male β_1 , family size β_2 , log familyincome β_3 , log familyincome ² β_4 .	Between individual variance (u_{6jkl})	Use command window and survival macro to set model up. Use equations window	$\beta_0 = 4.427 (0.001)$ $\beta_1 = -0.057 (0.002)$ $\beta_2 = -0.001 (0.001)$ $\beta_3 = 0.017 (0.002)$ $\beta_4 = 0.002 (0.000)$ $u_{6jkl} = 0.008 (0.000)$	4 seconds
Three level log duration model with individuals nested within households within parishes	$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$.	u_{6jkl} , between household variance v_{0kl} , between parish variance f_{0l}	As above and added specified additional 2 levels in equations window	$\beta_0 = 4.429 (0.001)$ $\beta_1 = -0.0581 (0.002)$ $\beta_2 = -0.001 (0.001)$ $\beta_3 = 0.0163 (0.002)$ $\beta_4 = 0.002 (0.0003)$ $f_{0l} = 0.0000071 (0.0000070)$ $v_{0kl} = 0.004 (0.002)$ $u_{6jkl} = 0.005 (0.0002)$	6 seconds

4. Documentation and user support

MLwiN is one of the best supported multilevel packages available. The documentation that is freely available for the software is summarised in the table below.

Document name	Hard copy?	On-line downloadable?	Document Size (Pages)
<i>A User's Guide to MLwiN Version 2.0</i>	YES	YES	250
<i>MCMC estimation in MLwiN</i>	NO	YES	297
<i>Modelling survival data in MLwiN 1.20</i>	NO	YES	29
<i>MLwiN 2.0 Command Manual</i>	NO	YES	114

The basic manual (Rasbash et al. 2003a) as evolved over the years into its current 250 page form. Of course it acts as a guide to the software. However, perhaps more importantly, it also introduces users to the concepts and applications of multilevel modelling. There are 19 chapters with the first 8 covering more basic modelling concepts and the final 11 dealing with more advanced model types. The latest release of the manual mostly deals with models fitting using the default Iterative Generalised Least Squares (IGLS) estimation method with a relatively brief overview of simulation methods being presented towards the end.

Previous releases of the manual contained a number of chapters dealing with Markov Chain Monte Carlo (MCMC) methods, which allow Bayesian models to be fitted where prior distributions for the model parameters are specified. With the latest release of the software, the MCMC documentation has been expanded and moved to its own manual (Browne, 2003). The document weighs in at 297 pages, longer than the main introductory manual. It contains some relatively advanced statistical theory but less advanced users can ignore much of this and concentrate on the more practical elements. The functionality of MCMC methods has been expanded in the new *MLwiN* release and a number of models, such as those involving cross classification, are now much easier to fit using MCMC than they were with IGLS. The basic manual has not as yet been fully updated to reflect this and contains a short chapter on the rather involved process of setting up cross classifications in IGLS, when in fact this can be done by selecting a single menu option when using MCMC estimation. For those users wishing to analyse survival data a further 29 page manual is available which covers the various types of survival model that it is possible to fit in *MLwiN* (Yang & Goldstien, 2003). There is also a command language manual providing an overview of commands that can be used to construct macros (Rasbash et al. 2003b) The latest versions of the all manuals are downloadable from the Centre for Multilevel Modelling website (details below) in the form of Adobe Acrobat pdf files. Also on the website are a number of downloadable research papers covering various more theoretical aspects of multilevel analysis.

The website run by the Centre for Multilevel Modelling (<http://multilevel.ioe.ac.uk>) is very comprehensive. It contains a brief introduction to multilevel modelling with a number of links to other useful websites. There is a section describing *MLwiN* and users can order the package on line. The 'downloads' area allows the latest version of the software to be downloaded at no charge by users who have already purchased a copy. The latest versions of the manuals, plus sample datasets and macros to accompany them, can also be found here.

Face to face user support is provided in two ways. A free monthly clinic, designed to help users of *MLwiN* analyse their data, is held at the Institute of Education in London, normally on the first Wednesday of the month. The clinic is run on an appointment basis. There is also multilevel modelling discussion list which can be joined on the jiscmail service. Although not restricted to *MLwiN*, is still a good place for finding solutions to problems and extending understanding. For users wanting more fundamental training on general multilevel modelling concepts and their application in *MLwiN* a number of workshops are run each year at Universities, both in Great Britain and abroad. These typically last for 3 days and cost £600 with a 40% academic discount.

5. Cost and contacts

A free training version of *MLwiN*, which only operates with sample datasets, can be downloaded from the Teaching Materials and Resources for Social Sciences (TRAMSS) website at <http://tramss.data-archive.ac.uk/documentation/download/index.asp>. The full version of *MLwiN* can be ordered on line from the multilevel website detailed above. It currently costs £500 (\$900, €900) for a single user licence + manual, with additional licences and manuals being available at £120 (\$216, €116). A 50 copy site licence costs £1750 (\$3150, €3150), and this can be extended to 250 copies with payment of an additional £1750 (\$3150, €3150). Additional manuals can be purchased for £25 (\$45, €45) a copy.

For further information, check the website, or contact:

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