Module 15: Multilevel Modelling of Repeated Measures Data

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Pre-requisites

- Module 5

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Contents

Introduction

In Module 5 models for two-level hierarchical data were introduced, with applications to structures with individuals at level 1 and some grouping of individual (e.g. countries or schools) at level 2. In this module we consider two-level structures arising from longitudinal studies where there are repeated measurements on individuals. Such studies lead to structures where the measurement occasions form the level 1 units and individuals are shifted up to level 2. The methods described in this module can also be applied in the analysis of data from repeated cross-sectional designs where the units being repeatedly measured are aggregations of individuals such as countries or institutions.

This module is organised into two parts, with each focusing on a different approach to analysing change in a continuous response over time. In Part I we consider **growth curve models**. The basic growth curve model is a type of random slopes model, where the predictor of major interest is some measure of time (e.g. an indicator of the measurement occasion or a subject's age when a particular measurement was taken). An important issue when applying multilevel models to longitudinal data is that the model should capture the correlation structure within individuals. As level 1 units (measurement occasions) are temporally ordered within level 2 units (individuals), it will usually be unreasonable to assume an equal correlation between the responses for any pair of occasions for a given individual: we would expect the correlation to decrease as the length of time between occasions increases. We will pay particular attention to this feature of longitudinal data when describing different types of growth curve model. The application of growth curve models is illustrated in analyses of children's reading progress with age.

Part II focuses on **dynamic models** (also called autoregressive response models). In a dynamic model the response at occasion t is a function of lagged outcomes, most commonly the response at the most recent occasion $t-1$. Random effects dynamic models can be used to distinguish two sources of within-individual dependency in responses: a direct effect of previous responses on a later response (state dependence) and unmeasured individual traits that are fixed across the observation period (unobserved heterogeneity). Dynamic models are widely used when there is interest in the effects of changes in time-varying covariates on change in the response variable. We illustrate the use of dynamic models in a study of the effect of changes in employment status (e.g. job loss) on mental health, after adjusting for mental health before employment change.

Although we describe both growth curve models and dynamic models as multilevel models, it is possible to frame both types of model as structural equation models (SEM). The data may be organised differently according to whether the model of interest is viewed as a multilevel model or a SEM, and different software used for estimation, but the underlying model is the same. In this module we mention SEM only in passing, and refer to other authors who have demonstrated the equivalence of the two approaches.

Introduction to the Example Datasets

Reading development of U.S. children

Growth curve analysis will be illustrated using data from the U.S. National Longitudinal Study of Youth (NLSY). The original study began in 1979 with a nationally-representative sample of nearly 13,000 young people aged 14 to 21. We consider data from a sub-study of children of the female NLSY respondents which began in 1986 when the children were aged between 6 and 8 years. Child assessments were then administered biennially in 1988, 1990 and 1992. We will analyse a sub-sample of 221 children who were assessed on all four occasions.

We consider the following variables:

- *read*. The child's reading recognition skill measured using a subtest of the Peabody Individual Achievement Test. The reading recognition subtest measures word recognition and pronunciation ability.
- *anti*. A measure of the child's level of antisocial behaviour, measured using a subtest of the Behaviour Problems Index. This variable is based on mother reports of behaviour over the previous three-month period.
- *male*. The child's gender (coded 1 for male, and 0 for female).
- *homecog*. A measure of the degree of cognitive stimulation provided to the child at home, based on mother reports.

Further details of the study design and measures can be found in supporting documentation.[1]

[1] Documentation written by Patrick J. Curran for a symposium on "Comparing three modern approaches to longitudinal data analysis: An examination of a single developmental sample": http://www.unc.edu/~curran/srcd-docs/srcdmeth.pdf

Mental health of British men

The application of dynamic (autoregressive response) models will be illustrated using data from the British Household Panel Survey (ISER, 2010).[2] We consider annual data for a random sub-sample of 2000 men for the period 1991-2009 (waves 1 to 18). The focus of the analysis is the effect of employment change on mental health, and thus the sample was restricted to men of working age (16-64) after leaving full-time education.

We consider the following variables in the analysis, all of which were collected annually:

- *GHQ*. A self-reported measure of anxiety and depression from an instrument called the General Health Questionnaire. We use the summative score of 12 items coded (0-1-2-3), leading to a variable with range of 0-36 where higher values indicate poorer mental health.
- *Employment status*. We distinguish three categories: (i) employed full-time or part-time, (ii) unemployed, and (iii) out of the labour market (i.e. not in employment or available for work). The major reasons given for being out of the labour market are long-term sickness and early retirement.
- *Change in employment status in the last year*. Dummy variables derived from employment status after grouping together categories (ii) and (iii) above to form a 'non-employed' category. We therefore consider four categories of change (including no change): remained employed, employed to non-employed, non-employed to employed, and remained non-employed.
- *Age in years*.

The data are a subsample of the dataset analysed in a study of the relationship between employment transitions and mental health (Steele, French and Bartley, 2013).

[2] The data may be downloaded by registered users from the UK Data Archive http://www.data-archive.ac.uk/

C15.1 Overview of Repeated Measures Data and Methods

C15.1.1 Repeated measures data structures

Repeated measures data are often available in the form of one record per individual, with each time-varying measure stored as a set of variables, one variable for each measurement occasion. This individual-based data structure is commonly referred to as ‘wide’ form. Table 15.1 shows an extract of the reading data in this form, where the reading scores for the four occasions are stored in variables **read1** to **read4**.

Table 15.1. Reading data for two children in wide form

Child	male	homecog	read1	read2	read3	read4
1	1	9	2.1	2.9	4.5	4.5
2	0	7	2.3	4.5	4.2	4.6

For a multilevel analysis, the data need to be restructured so that there is a record for each measurement occasion, referred to as ‘long’ form. Table 15.2 shows the data of Table 15.1 in long form, with four records per child. The data in **read1** to **read4** have been stacked into a single variable **read**, with the different occasions indexed by **year**. Values of the time-invariant child characteristics (**male** and **homecog**) are repeated across years. After restructuring we can see that repeated measures data have a two-level hierarchical structure with occasions (indicated by **year**) at level 1, nested within children (identified by **child**) at level 2. It is straightforward to convert data from wide to long format in most statistics packages.

Table 15.2. Reading data for first two children in long form

child	year	male	homecog	read
1	1	1	9	2.1
1	2	1	9	2.9
1	3	1	9	4.5
1	4	1	9	4.5
2	1	0	7	2.3
2	2	0	7	4.5
2	3	0	7	4.2
2	4	0	7	4.6

In general, there will be missing data due to some individuals not participating in one or more waves of the study. In wide form, this would result in missing values for any of **read1** to **read 4**. After converting to long form, the records for occasions when an individual was not present can be deleted from the dataset. There is no requirement in a multilevel analysis to have balanced data, so individuals who contribute fewer than the maximum number of observations can be retained in the analysis without further adjustment. However, while this is common strategy, it should be recognised that such an analysis makes a 'missing at random' assumption.[3]

C15.1.2 Examples of research questions and methods

The following are examples of research questions that can be investigated through analysis of repeated measures data.

(i) To what extent does the rate of cognitive development vary between children?

(ii) Does the rate of cognitive development differ for boys and girls?

(iii) What is the effect of employment status on mental health, controlling for prior mental health?

(iv) What is the effect of a *change* in employment status (e.g. job loss) on mental health, controlling for prior mental health?

Questions (i) and (ii) relate to change in a cognitive outcome during childhood, and how that change varies across different groups (defined by gender here). We would expect a monotonic increase in such outcomes with age, although children will vary in their starting points and their growth rate. Growth curve models are a natural approach to analysing developmental outcomes.

Questions (iii) and (iv) concern the effect of a time-varying predictor variable employment status (or change in employment status) on mental health. Because people in poor mental health may have a tendency to be out of employment (or to leave employment), it is usual in such analyses to condition on prior mental health. In an autoregressive model, the response at the previous occasion (and possibly occasions prior to that) is included as a predictor. Furthermore, mental health would not be expected to show a monotonic increase or decrease. While there will be differences between individuals in their mental health at any given time point, within-individual change is likely to fluctuate in response to time-varying factors such as major life events. Autoregressive models are used when the focus is on the effects of time-varying predictors and the dependency in an individual's responses over time is expected to be explained by a combination of the effect of previous responses and the effect of time-invariant unmeasured individual characteristics.

[3] Response y_{ij} is said to be missing at random if the probability of missingness depends on observed covariates and non-missing values of y (e.g. responses at earlier occasions), but not on the unobserved response y_{ij}. For a discussion of missing data mechanisms in a longitudinal setting see Chapter 14 of Hedeker and Gibbons (2006). See also Module 14 (C14.7) on multiple imputation (with accompanying practicals in Stata and MLwiN).