Multilevel Models: Conceptual Framework and Applicability

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Abstract: Individuals and the social or organizational groups they belong to can be viewed as a hierarchical system situated on different levels. Individuals are situated on the first level of the hierarchy and they are nested together on the higher levels. Individuals interact with the social groups they belong to and are influenced by these groups. Traditional methods that study the relationships between data, like simple regression, do not take into account the hierarchical structure of the data and the effects of a group membership and, hence, results may be invalidated. Unlike standard regression modelling, the multilevel approach takes into account the individuals as well as the groups to which they belong. To take advantage of the multilevel analysis it is important that we recognize the multilevel characteristics of the data. In this article we introduce the outlines of multilevel data and we describe the models that work with such data. We introduce the basic multilevel model, the two-level model: students can be nested into classes, individuals into countries and the general two-level model can be extended very easily to several levels. Multilevel analysis has begun to be extensively used in many research areas. We present the most frequent study areas where multilevel models are used, such as sociological studies, education, psychological research, health studies, demography, epidemiology, biology, environmental studies and entrepreneurship. We support the idea that since hierarchies exist everywhere, multilevel data should be recognized and analyzed properly by using multilevel modelling.

Keywords: multilevel data; nested data structure; group correlations; multilevel analysis

JEL Classification: C19; C51

1. Introduction

Socio-economic phenomena may occur at many levels: persons, family, neighbourhood, city, society. Individuals and the social or organizational groups they belong to can be viewed as a hierarchical system situated on different levels. Individuals are situated on the first level of the hierarchy and they are nested together on the higher levels. Individuals may be nested in rural or urban areas, cities, states, regions, countries, or may be grouped within organizations, trade unions, political parties or some other type of social group.

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The nesting of individuals in social groups generates a mutual relationship between individuals within the same group, but also between individuals and the society as a whole; there can be observed a correlation between the characteristics of the individuals and the characteristics of the group to which they belong. Individuals interact with the social groups they belong to and are influenced by these groups (Hox, 2010, p. 1): the social context or the group may influence individuals' opinions, actions and behaviour. Social groups are themselves influenced by individuals in the group (Hox, 2010, p. 1).

The analysis of socio-economic phenomena implies therefore the analysis of complex data sets that have a hierarchical structure. Such analyses should consider each level of the hierarchy, together with their interactions.

Reality can be described through conceptual models of data. Traditional linear models such as analysis of variance and linear regression offer a simple view of a complex world by generally assuming the same effects across groups. Hierarchical data no longer satisfy the independence hypothesis. Clustered data structures are defined by the dependence of observations within groups or units. Hence, in the case of hierarchical data, when effects differ across groups, multilevel models should be used to analyse and explain these differences. By applying multilevel analysis we can investigate the variables measured at different levels of the multilevel data structure and the relations between them. Ignoring the effects of nested data may lead to biased estimates in the case of traditional single level models. Multilevel modelling corrects the bias of the estimates, the bias of the standard errors and leads to more accurate test results and conclusions.

Multilevel analysis is quite common in sociological studies, education, psychological research, health studies; the multilevel approach is also used in demography, epidemiology, biology, environmental studies, as well as in entrepreneurship research. Educational studies were among the first to use multilevel models and such examples are introduced in many papers (Aitkin, Longford, 1986; Raudenbush and Bryk, 1986, Goldstein, 2003; Gelman and Hill, 2007; De Leeuw and Meijer, 2008; Snijders and Bosker, 2012; Hox, 2010). In addition to these research papers and manuals, statistical analysis software such as MLwiN, HLM, S-Plus, GLAMM, GenStat were also developed to analyse multilevel data. The new IT technologies offered statistical researchers a greater accessibility and faster tools for the implementation of multilevel analyses.

2. Multilevel Data

The term “multilevel” is associated with a nested data structure, but the nesting may also consist of repeated measures within subjects or longitudinal data.

A hierarchy is a structure of units or individuals grouped in two or more different levels. The classic example of a simple data hierarchy with two levels, often addressed in educational studies, is that of students nested in schools. Other examples of two level data are individuals nested within countries or households, patients nested under hospitals, employees nested within organizations, families nested in neighbourhoods.

Crossed data, that is individuals belonging to several higher levels, are also multilevel data. An example of a crossed data structure is that of students nested within the same school, but belonging to different regions. In this case both schools and regions are on the second level of the hierarchy.

Multiple membership data are also multilevel data. Multiple membership data assume that individuals belong to several groups, such as students that can move from one school to another and from one region to another during the same study period; they belong, therefore, to several regions and to several schools. The three types of multilevel data structures – hierarchical data, crossed data, multiple membership data - are shown in the diagrams from Figure 1.

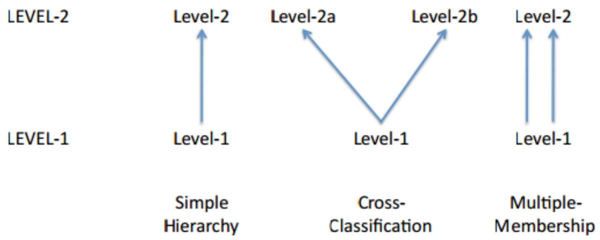

Figure 1. Multilevel data structures

Source: Centre for multilevel modelling, University of Bristol - Multilevel structures and classifications

Repeated measurements on units or individuals are also two level data: the measurements are situated on the first level of the hierarchy and the individuals on the second level. Multivariate responses of individuals can be considered two level data as well: responses of an individual are the first level and the individual represents the second level of the hierarchy.

Longitudinal data consists of repeated observations of the same variables over long periods of time: time is the first level of the hierarchy and the individual is the second level. Time is thus nested within individuals.

3. Multilevel Analysis and Multilevel Models

Data modelling is the process that translates a real phenomenon into a conceptual model. The model is a simplified representation of reality that captures the essential aspects of the phenomenon or the research process. In statistical analysis, a model involves dependent and independent variables and the relationships or the links between them. The relationships between variables and their characteristics are expressed through the equation or through the system of equations that defines the model.

The term “multilevel model” is a general term used for all models that work with nested data. The multilevel model is a generalized single level regression that takes into account the grouping of data at a higher level. The multilevel model is known as the mixed model, the variable coefficients model (De Leeuw and Kreft, 1986), the variance component model (Longford, 1987) or the hierarchical linear model (Raudenbush and Bryk, 1986).

There are several categories of multilevel models according to the data type of the response variable: data with three or more levels, crossed data, multiple membership data, multivariate response models, multilevel models for repeated measures, discrete response models, time series models, factor analysis models. Also, according to the type of distribution for the response variable, multilevel models can be classified as: multilevel models for normally distributed response variables or multilevel models for binary, binomial, ordinal, nominal or Poisson response variable. If the response variable has any distribution other than the normal distribution, the models are called generalized multilevel models.

Multilevel models are designed to simultaneously analyse variables at different levels, properly including various dependencies (Hox, 2010: 6). Multilevel analysis applies to multilevel data structures and models the group’s influence on the individual response. Individuals of the same group are similarly influenced by the same factors and hence the response data is not independent anymore, as in ungrouped data. By using multilevel analysis we can investigate the level 1 characteristics that affect the outcome, the level 2 characteristics that influence the outcome and also the level 2 characteristics that influence the level 1 intercepts and slopes. We perform multilevel data analysis to assess the amount of variability due to each level, to model the level 1 outcome in terms of effects at both levels or to assess interaction between level effects.

There is no “adequate” level where data should be analysed, but all levels are important in their own way (Hox, 2010: 4). As a generalization of regression, multilevel modelling can be used in forecasting, data reduction or for causal inference. Forecasting is perhaps the most obvious advantage of multilevel modelling (Gelman, 2006: 432). Using single level methods of analysis for multilevel data leads to some adverse consequences (Maas, Hox, 2004: 128): parameter estimators are unbiased but inefficient (de Leeuw, J. and Kreft, 1986; Snijders and Bosker, 2012; Hox, 2010) and contextual information cannot be properly modelled and ends up in the error term.

A nested structure leads to the correlation of data within a group. The single level traditional statistical methods of analysis disregard these correlations and they result in biased estimates and large standard errors and may consequently lead to incorrect tests and conclusions. Obtaining small standard errors is one of the reasons for using multilevel modelling (Steele, 2008).

3.1. The General Two-Level Model

A multilevel model applies to grouped data with two or more hierarchical levels. The variables in the model can be found at any level of the hierarchy. Multilevel models allow simultaneous assessment of the effects of individual and group variables on the response variable.

All multilevel models assume a hierarchical data set, with one single outcome or response variable that is measured at the lowest level, and explanatory variables at all existing levels. The basic multilevel model is the two-level model. The simplest multilevel model is the null model, a model with no predictors.

The equations for the two-level null model are as follows:

Level 1 equation: $Y_{ij} = \beta_{0j} + e_{ij}$ (1)

Level 2 equation: $\beta_{0j} = \beta_0 + u_{oj}$, (2)

By substitution of equation (2) in equation (1) we get the final equation:

$$Y_{ij} = \beta_0 + u_{oj} + e_{ij} \quad (3)$$

where i=1,…., I level 1 units,

j=1,…, J level 2 units,

Y – dependent variable, X – independent variable,

e – level 1 error, $e_{ij} \sim N(0, \sigma_e^2)$, $var(e_{ij}) = \sigma_e^2$,

u – level 2 error, $u_{oj} \sim N(0, \sigma_{u0}^2)$, $E(u_{oj}) = 0$; $var(u_{oj}) = \sigma_{u0}^2$.

Equation (3) has a fixed component (β_0) and a variable component ($u_{oj} + e_{ij}$).

When adding one or more independent variables into the null model we get the general equations (5), (6), (7) for the two-level model.

Level 1 equation: $Y_{ij} = \beta_{0j} + \sum_{h=1}^{n} \beta_{h,j}\, x_{h,ij} + e_{ij}$(5)

Level 2 equations: $\beta_{0j} = \beta_0 + u_{oj}$, (6)

$\beta_{hj} = \beta_h + u_{hj}$, (7)

where: i=1,…., I level 1 units,

j=1,…, J level 2 units,

h=1,…, H number of independent variables,

Y – the dependent variable, X – the independent variable

e – level 1 error, $e_{ij} \sim N(0, \sigma_e^2)$, $var(e_{ij}) = \sigma_e^2$

u – level 2 error, $u_{hj} \sim N(0, \sigma_{u0}^2)$, $E(u_{oj}) = E(u_{1j}) = 0$;

$var(u_{oj}) = \sigma_{u0}^2$; $var(u_{1j}) = \sigma_{u1}^2$; $cov\,(u_{oj}, u_{1j}) = \sigma_{u01}$;

If we substitute equation (6) and (7) into equation (5), we get the final equation (8):

$Y_{ij} = (\beta_0 + u_{oj}) + \sum_{h=1}^{n}(\beta_h + u_{hj}) + e_{ij}$ (8)

By grouping the fixed effects and the random effects terms we get (8):

$Y_{ij} = (\beta_0 + \sum_{h=1}^{n} \beta_h X_{h,ij}) + (u_{oj} + \sum_{h=1}^{n} u_{h,j} X_{h,ij} + e_{ij})$ (9)

fixed effects variable effects

The two-level model can be further extended by adding more levels and more independent variables that can vary at the higher levels.

4. The Applicability of Multilevel Models

Multilevel modelling is intensively applied to real problems from social and human sciences, health sciences, agriculture and medicine. Educational research is where multilevel analysis started to develop: the classic multilevel examples refer to students grouped in classes, classes grouped in schools, schools grouped in school districts. School effectiveness research can be done most effectively using a multilevel model (Goldstein and Spiegelhalter, 1996).

The sociological theories of psychiatric illness and delinquency arising out of the Chicago School introduced the idea that individual actions are shaped by the influences of macro-level forces (Faris, Dunham, 1939; Shaw, McKay, 1969). These theories suggest that both individual as well as social context factors can affect individual health and criminal behaviour (Moineddin et al, 2007).

Biological, psychological and social processes that influence health occur at several levels: cell, organ, individual, family, neighbourhood, city, company level. An analysis of risk factors should consider each of these levels as well as their interactions. The health system has a hierarchical structure: patients are grouped within doctors, the doctors are nested within hospitals or by practice. Multilevel models have also been intensively used in epidemiology in the last decade, being suitable for analysing the influence of context on individual health (O'Campo, 2003).

In environmental and ecological research assumes interactions between different measurement scales: ecosystem processes involve interactions at multiple scales and hence the multilevel approach is justified for predictive modelling as well as for the flexibility of defining the model (Qian et al, 2010).

Multilevel modelling is also used in team organization research. Team performance can be understood and more effectively managed by considering the complex relationships between organizational practices and technological tools, and between individual and team characteristics (Griffith and Sawyer, 2010). Training and learning processes can also be modelled by using multilevel modelling (Chen et al, 2005; Kozlowski et al, 2000; Lapointe and Rivard, 2005), as well as expertise recognition and usage (Bunderson, 2003), as well as examination and support of team members (Van der Vegt et al, 2006).

In the case of entrepreneurship, the multilevel tools that take into account both the individual level characteristics, as well as the entire context where these characteristics influence the actions and the behaviour of the entrepreneur. Multilevel models can provide a more robust and vast understanding of why and by what conditions some people are interested in developing the entrepreneurial activity (Klein et al, 1999). Individuals and organizations affect and are affected by their social context. The role of informal institutions on entrepreneurship is discussed by Autio and Wennberg (2010); they develop and test a multilevel model for entrepreneurial behaviour that takes into account the attitudes of the social group as well as behavioural norms that influence the individual.

Many research topics in political science can be studied on several levels. Political science theories rely on the assumption that the variables measured at one level can influence or link to variables from other levels. The political science unit can be defined in geographical terms (country, region, state), in temporal terms, such as election periods or in social terms, such as political or social groups. Multilevel data structures especially exist in comparative analyses in the political science area (Jones et al, 1997).

Ignoring the variation of the response variable between countries when analysing the relationship between the independent variables and the economic conditions, such as unemployment, may lead to incorrect or inaccurate inferences. Since the "contextual factors" highly vary between countries (Przeworski et al, 2000), there will be different influences on the surveyed countries.

Election results can be modelled by considering individuals as nested in campaigns or election periods. If individuals respond or react differently to different national contexts (Kramer, 1983; Haller and Norpoth, 1994) or to different political campaigns (Kahn and Kenney, 1999), then regional or national political factors may lead to variation of individual level variables. Hence, the comparative analysis of election periods or of more national campaigns calls for multilevel data analysis.

The analysis regarding the influence of religion or the social class on the voting decision shows that these factors reduced their intensity (Goldberg, 2014). To analyse the impact of religion on the decision to vote for the Swiss Christian democrat party, Goldberg uses a hierarchical linear model, a model that takes into consideration the individual variables, as well as the contextual effects. The voting data corresponds to the 2007 and 2011 elections and the results confirm the influence of the individual variables on the voting decisions, as well as a considerable contextual effect

A very popular topic in the UK is the influence of local context on political reaction and voting behaviour. Multilevel modelling assesses both the importance of the voter's characteristics and the environmental characteristics, independently of attitudes and behaviour. Using the 1987 national election data, Jones et al (1992) shows that the place is important as part of the mechanism that influences individual's vote. Multilevel modelling is necessary to study the electoral behaviour. Least squares regressions do not take into consideration date correlation and cannot divide the variation of the response variables between hierarchy levels. Through regression one cannot separate the influence of the individual characteristics and the background influence on the choice of voting. Multilevel analysis can show that the individual effects are not the only influencers of votes. The voter has his own choice but this is made in a certain context that influences therefore the voter's choice (Jones et al, 1992).

Other studies that make use of multilevel models are studies on the European integration. These studies involve either aggregated data with emphasis on cross-national variation and time trends regarding the support for integration (Eichenberg and Dalton, 1993) or individual data with emphasis on factors that may influence individuals to support the European Union integration (Deflem and Pampel, 1996; Janssen, 1991). Studies show that the effect of political ideology (left or right ideology) towards EU support is weak (Wessels, 1995; Deflem and Pampel, 1996). Political ideology may have an important positive or negative influence only in some countries. If the variance component corresponding to the ideology is statistically significant there is contextual variation and hence the country level factors causing this variation may be assessed.

The performance of the Romanian ICT companies is evaluated by using multilevel models so as to analyse the micro and macro level interactions that exist in this field

(Mazurencu, Pele, 2012; Mazurencu, 2013). The integrated performance of the metropolitan areas is analysed by using advanced growth models which are also multilevel models (Kourtit, Mazurencu, Nijkamp, 2014). This research takes into consideration 35 cities all over the world: the data collected from the GPCI database is analysed by using the R statistical program.

5. Conclusions

Many types of data have a hierarchical or nested structure. This hierarchical structure of the society generates a correlation between individuals within the same group. Individuals are influenced by the group they belong to and, in turn, social groups are themselves influenced by the individuals in the group (Hox, 2010, p. 1).

Multilevel models capture the dependence of observations within groups by using higher level variables and also analyse the influence of higher level variables on the response variable. These models can also estimate the interaction between levels which means a joint effect of an individual variable and of a higher level variable on the response variable. With multilevel models, variables may be defined and may vary at any level, each level being a potential source of variability.

For grouped data, multilevel analysis is considered more reliable than a single-level analysis; the accuracy of results with multilevel analysis can be higher (Goldstein, 2003). This feature is especially important in social studies that are vast in scope and cannot be assessed with single-level models.

The existence of data hierarchies is neither accidental nor can be ignored (Goldstein, 2003) and the bottom line is that multilevel models are a necessity in many research areas. As such, multilevel models are used to model real problems from education, social and human sciences, health sciences, agriculture and medicine. Health can be influenced by factors existing at several levels: cell, organ, individual, family, neighbourhood, city, company level. Ecological research relies as well on the multilevel modelling framework, as the ecosystem processes involve interactions at multiple scales. Team performance, training and learning processes can also be modelled by using multilevel modelling. Individuals and organizations affect and are affected by their social context. Multilevel models can hence provide a more robust and vast understanding of why and by what conditions some people are interested in developing the entrepreneurial activity (Klein et al, 1999).

Many research topics in political science can be studied on several levels, such as electoral studies or the voting behaviour of the individual. Political science theories rely on the assumption that the variables measured at one level can influence or link to variables from other levels. Multilevel analysis can show that the individual effects are not the only influencers of votes. The voter has his own choice but this is made in a certain context that influences therefore the voter's choice (Jones et al, 1992). Economic research can as well be developed on nested data, as individuals are naturally grouped within administrative or geographical units and the "contextual factors" highly vary between countries (Przeworski et al, 2000).

Since hierarchies exist everywhere, this makes it possible for multilevel theory to continuously extend for research purposes. Researchers need to acknowledge that if so many research topics are of multilevel nature, multilevel theories and methods of analysis should be used (Luke, 2004: 4).

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