

### Understanding time as socio-historical context: analyzing social change within the framework of multilevel analysis

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Understanding time as socio-historical context:  
Analyzing social change within the framework of  
multilevel analysis

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# Understanding time as socio-historical context: Analyzing social change within the framework of multilevel analysis

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## **Abstract**

From a methodological and sociological perspective, analyzing social change is best done by using repeated cross-sectional data and by including individual level variables, time, and time-dependent macro variables. Furthermore, interest often focuses on whether the effects of explanatory variables change over time, e.g. the impact of education on one's social position. We argue that multilevel models with time as context best meet these requirements. However, the methods for applying a multilevel approach to study time-dependent social processes are relatively poorly developed and therefore rarely used. Instead, most social change related analyses of repeated cross-sectional data, such as APC models or changing effect models, include time as an individual level variable and thereby neglect the contextual characteristics of time and changes at the macro level. In contrast, pooled time series analysis does not take account of individuals and micro level effects. Thus, the aim of this paper is to overcome these shortcomings by adopting a new approach to social change studies. We describe the application of multilevel analysis with years as contextual units on a step-by-step basis and emphasize the substantive advantages of each model for the study of social change.

## 1 Introduction\*

As sociologists, we aim to analyze, understand, and explain issues related to social change. To achieve this objective, we require theories on our subject, appropriate methods to transform our theoretical models into statistical models, and repeated cross-sectional data to test our hypotheses.

Following the theory of Boudon (1986, 1983) and the general logic of sociological explanation of Coleman (1994, 1987), explanations of macro level phenomena, such as the expansion of educational opportunities, can be generated only by taking into account the actions and characteristics of individuals at the micro level. Simultaneously we have to consider the socio-historical context or, respectively, the changing structural parameters which, at a given point in time, restrict or facilitate certain courses of individual action. We argue that multilevel models with time as context are best suited to fulfilling these theoretical requirements.

However, the methods for applying a multilevel approach to study time-dependent social processes are relatively poorly developed and therefore rarely applied. For example, the repeated cross-section case to analyze social change is discussed in none of the textbooks on multilevel analysis (Goldstein 2011; Hox 2010; Raudenbush and Bryk 2002; Snijders and Bosker 1999; Kreft and De Leeuw 1998). On the other hand, the standard approaches to the study of social change do not recognize the inherent multilevel structure. They focus on changes at either the micro level or at the macro level. Further, these methods only allow rather descriptive analysis. Accordingly, the objective of this paper is to overcome these shortcomings and propose an approach that closes the gap between social change theory and statistical modeling, thereby increasing our knowledge of social change processes.

In this methodological-conceptual paper, we discuss how to study social change properly and argue that multilevel techniques are particularly well suited for this purpose. Given that multilevel models are more complex than standard single level methods, we introduce and discuss different ways to set up these models. Therefore, our focus is on model specification. Though many of the points will not be new to experts in multilevel modeling, our aim is to provide an opportunity for reflection on the kinds of social change-related questions we might ask and on the potential of multilevel models to provide answers to them.

The paper is structured as follows: First, we show that the standard approaches to studying social change have several shortcomings (Chapter 2). Second, we give an overview

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of the multilevel approach to the repeated cross-section case (Chapter 3). In the course of this presentation, we introduce the step-by-step application of multilevel analysis with years as contextual units. For each model specification we illustrate its substantive potential, using the rising levels of poverty among families in Germany as an example. We close the third chapter with a discussion of the problems connected with multilevel methods in social change studies.

## **2 Standard approaches to the study of social change**

Social change, that is the change of aggregates (e.g., percentage below the poverty threshold), can best be studied with repeated cross-sectional surveys representing a given population at a given time and a constant set of indicators (Firebaugh 1997, 2008: 172 et seq.). Typical cases of such a design are the so-called general social surveys, including the General Social Survey (GSS) in the United States, British Social Attitudes in the United Kingdom or the German General Social Survey (ALLBUS) (cf. Smith et al. 2005). Each new cross-section is representative of the entire population at the time of data collection, so a comparison of these samples over time reveals social changes. By selecting a fresh sample each year, repeated cross-sections cannot follow specific individuals over time. Therefore, individual level change cannot be analyzed with repeated cross-sections. That is what panel data are designed to do.<sup>1</sup> In contrast to panel designs, repeated cross-sections do not suffer from attrition. Additionally, repeated cross-sections often span much longer time periods than panel studies could.

However, we have to be aware that the analysis of social change with survey data is only possible when measures of the phenomenon under study do not change, or as Tom W. Smith (2010: 1) has put it in his first law to study societal change: “The way to measure change is not to change the measure.” This principle means that the specific item or question of interest in our repeated cross-sectional survey should remain unchanged over time. In addition, the entire instrument and procedure (surveying, coding, etc.) should stay the same over time. However, changes in sampling, field work procedures, questions, and questionnaires occur commonly in even the most stable repeated survey programs.<sup>2</sup>

Even if we had data collected in exactly the same way over several decades, the comparability for every item in the survey might not persist over time. Language is not static but evolves; therefore, words change their meanings, and new terms come into fashion. For example, in the U.S., the term “negro” was replaced first by “black” and then by “African-

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<sup>1</sup> Unlike repeated surveys, panel surveys follow the same individuals over time.

<sup>2</sup> These changes can be driven by the desire to improve data quality, they can be necessitated by social or technological innovations (e.g., new population registers or the introduction of computer-assisted interviewing), or they can result from sloppiness and mistakes (see Smith 2010 for a more detailed discussion).

American”. In Germany, the term “Gastarbeiter” was replaced first by “Ausländer” and now by “Migrant”.<sup>3</sup> Surveys also have to reflect changes in institutions: In Germany, due to the introduction of a legal partnership status for homosexual couples, the typical categories for questions about marital status had to be changed, and when the voting age was lowered from 21 to 18, the sample frames had to be adopted accordingly. Thus, institutional and cultural changes can make it necessary to change survey measures in order to reflect social change. Smith (2010: 1) states this principle in his second law for studying societal change: “When constant measures produce non-constant measurement, change the measure to measure change.”

Taken together, the points we have raised make it clear that studying social change on the basis of survey data is a difficult endeavour. Researchers need to test the data they analyze critically, keeping in mind the changing meaning of indicators, and must understand the procedures employed in data collection and data preparation. This degree of difficulty is precisely why comprehensive data documentation is of the utmost importance for repeated surveys. Of course, carefully studying this documentation before drawing and interpreting results from trend analysis is of equal importance. Finally, researchers need a good (measurement and substantive) theory to draw valid conclusion from the data. However, these problems should not prevent us from exploring social change with the help of survey data. We are certain that using these data properly and critically will yield a wealth of valid findings and the potential to increase knowledge.

In the following parts of this chapter, we briefly present three traditional models used to analyze social change with repeated cross-sections: age-period-cohort analysis, changing parameter models, and time-series cross-section models. These approaches differ primarily in their unit of analysis (micro vs. macro level) and in their treatment of time.

### ***2.1 Analysis of age, cohort, and period***

What are the mechanisms leading to social change, i.e., changes in the population or the population’s characteristics? One possibility is that individuals might change their worldviews as they grow older. This intra-individual process, however, only leads to change on the aggregate level if the age distribution of the population changes, for example, through changing fertility rates. An alternative mechanism consists of a process called cohort replacement. For this mechanism to take effect, older birth cohorts have to be replaced by younger birth cohorts with different characteristics. Cohort replacement then leads to social

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<sup>3</sup> These terms can be translated as immigrant workers, foreigners and migrants, respectively.

change. Another mechanism leading to changes on the level of populations consists of events affecting the entire population. For example, the catastrophe in Fukushima has probably altered the attitudes of the German population toward nuclear energy. Because these three mechanisms can all operate at the same time, researchers have to find ways to disentangle their relative impact. As can be seen in the following equations, this is not a simple task.

Let us assume we are interested in the effects of age, cohort, and period on a characteristic,  $Y$ . This can be expressed in a linear model, the famous APC model:

$$Y = \beta_0 + \beta_1 \text{Age} + \beta_2 \text{Period} + \beta_3 \text{Cohort} + \varepsilon \quad (1)$$

The study of the three effects of age, cohort, and period has fascinated and plagued students of social change for a long time. This longstanding interest most likely stems from the identification problem and attempts to overcome it. The problem arises because age, period, and birth cohort are not linearly independent as the following equation shows:

$$\text{Age} = \text{Period} - \text{Cohort} \text{ or } \text{Cohort} = \text{Period} - \text{Age} \text{ or } \text{Period} = \text{Cohort} + \text{Age} \quad (2)$$

Thus, equation (1) is not solvable, i.e., it is impossible to estimate the relative effects of one of these three quantities while controlling for the effects of the other two. More precisely, it is impossible to study the relative importance of age, period, and cohort within the framework of equations (1) and (2), and much research has been conducted to find alternative models to overcome this situation. It is neither possible nor necessary to present all these different approaches here; interested readers are referred to the excellent overviews by Mason and Fienberg (1985), Hagenaars (1990), and Glenn (2005).

Research based on the APC approach frequently suffers from two problems. First, scholars often focus on age, period, and cohort and neglect other variables in their models. In principle, however, there is no limitation to the regression models used, and thus, the models could easily be extended. A second, more important issue concerns the effects of age, calendar year (period), and year of birth (cohort). From a theoretical point of view, these effects are not of particular interest. These variables do not explain why the phenomenon under study changes. Therefore, some authors have suggested replacing age, period, and cohort with more substantive variables such as education and cognitive ability. In effect, these approaches avoid the identification problem and might produce substantively richer explanations (for example, see O'Brien 2000).

## 2.2 *The changing parameter model*

In some instances, we might not be interested in disentangling age, period, and cohort effects but, instead, only want to know if the effect of a certain factor has changed over time. For example, it is often claimed that through the educational expansion, the effect of education on occupation has weakened, that is, the value of education has decreased – a phenomenon known as the inflation of education. Hypotheses of this nature can easily be studied by a so-called changing parameter model (Firebaugh 1997: 42-63). Assume that you have observational data for two points in time,  $t_0$  and  $t_1$ . Then this model with one explanatory variable can be expressed as:<sup>4</sup>

$$Y = \beta_0 + \beta_1 X + \beta_2 D + \beta_3 DX + e \quad (3)$$

$Y$  is the dependent variable in which we are interested.  $D$  denotes a dummy variable coded 0 if the observation comes from  $t_0$  and 1 if the observation comes from  $t_1$ .  $X$  is the independent variable we want to test, and  $DX$  is an interaction term coded 0 for all observations from  $t_0$  and  $X$  for all observations from  $t_1$ . Given this parameterization, the coefficients of the model have the following meaning: As usually  $\beta_1$  is the effect of  $X$  on  $Y$  at  $t_0$ ,  $\beta_0$  is the expectation of  $Y$  at  $t_0$ ,  $\beta_2$  is the difference between the expectation of  $Y$  at  $t_1$  and  $t_0$ , and finally  $\beta_3$  reflects the difference between the effect of  $X$  on  $Y$  at  $t_1$  compared to  $t_0$ . If this coefficient is significant, we can assume that the effect of  $X$  on  $Y$  has changed.

Within the context of our paper, this short sketch suffices to show that the changing parameter model allows us to test for changing effects from one or more variables between two points in time. However, the model has several limitations: First, it is not suited to study change between more than a few points in time. A longer time series, say 30 waves of data, requires comparing 29 regression coefficients (Firebaugh 2008: 182). Second, the approach includes time as an individual level variable and neglects changes at the macro level. Another limiting feature is that “this model is intended to document change, not to explain it” (Firebaugh 1997: 62). As we will see, multilevel models with years as contextual units and changing macro level conditions as contextual variables can be a promising additional step or supplement to determine the causes of the identified, changing effects (Chapter 3.3).

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<sup>4</sup> The extension of this model to multiple independent variables is straightforward.



### 2.3 *Time-series cross-section models*

An alternative approach to model social change over a longer time period is provided by time-series cross-section models. As the term indicates, time-series cross-section models (TSCS) combine two different types of data models: First, time-series, or data describing the development of one unit over time, and second, cross-sectional linear models, e.g., regular OLS regression with data for several units observed at one point in time. If these two types of data, longitudinal and cross-sectional, are combined, the result is a special form of data called TSCS data. In the words of one of its major proponents, “time-series cross-section (TSCS) data consist of comparable time-series data observed on a variety of units“ (Beck 2008: 475). This type of data resembles panel data but has two crucial differences. On a substantial level, the major difference pertains to the unit of analysis. While panel data are usually related to micro units (individuals), TSCS data are usually derived from macro units (such as countries). The second difference is more technical. Panel data usually consist of many units and only a few points in time (say, a panel of 5,000 respondents observed over 5 waves), while TSCS data typically are comprised of only a few units observed for a comparatively large number of points in time, e.g., EU-15 countries observed annually from 1980 to 2010.

TSCS models are applied to data with comparatively few (spatial or macro) units observed over a relatively large number of points in time. These observations are pooled across time and units into a single equation (Beck and Katz 1995: 636):

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + e_{it} \quad (4)$$

As in a regular linear regression model, the dependent variable  $Y$  is modeled on a set of independent variables  $X_j$ . In contrast to OLS models, however, there are multiple observations of the dependent and independent variables for each unit ( $i$ ), one for each point in time ( $t$ ). As can be seen in the equation above, it is assumed that the model holds for each unit and each point in time.

The basic question is how to estimate this model if one cannot assume that units are independent over time and/or in space, i.e., if one is dealing with correlated measurement error and possibly heteroscedasticity. In other words, TSCS data often violate the Gauss-Markov assumptions (Beck 2008: 478). While the estimates of the regression coefficients will be unbiased their standard errors will be inaccurate.

A common solution to these problems is to estimate the coefficients of the model using standard OLS; even with heteroscedasticity and correlated error the estimation of

coefficients will be unbiased. The standard errors, though, will normally still be considerably underestimated. As a remedy, Beck and Katz (1995) originally proposed using panel corrected standard errors. Meanwhile, a number of alternative approaches to correct standard errors in the case of serial correlation and heteroscedasticity have been developed (Wooldridge 2009: 428-437; Beck 2008; Engelhardt 2004).

The TSCS design is especially well suited to looking at social change when there are many observations through time. It also enables explicitly modeling changes through time. However, this design is restricted to macro level variables and does not allow the underlying processes at the individual level to be modeled, which runs contrary to Boudon and Coleman's logic of the sociological explanation of social change (Boudon 1986, 1983; Coleman 1994, 1987). Therefore, these models cannot tell us anything about the relative importance of individual change, aggregate change, and their interaction.

#### ***2.4 Shortcomings of the standard approaches***

The three standard approaches we have presented here have been used in innumerable studies of social change. They are powerful tools and easy to use (with the possible exception of TSCS). However, as we have attempted to show in this brief review, none of these approaches is fully satisfactory. APC analysis and changing parameter models focus exclusively on individual level data and are oblivious to macro level processes. In addition, time is treated as variable in these models but not as unit of analysis and, thus, is not causally interpretable. TSCS models operate differently. Here, time is treated as one dimension of the units analyzed, such as the unemployment rate in the year 1995. However, TSCS does not allow individual level characteristics to be included or dependencies of macro and micro characteristics to be modeled. To overcome these problems, we propose combining these approaches by integrating individual level and macro level models in which time is treated as a unit or a context of analysis. In the remainder of this paper, we will demonstrate that this can best be done in the framework of multilevel models.

### **3 Analyzing social change within the framework of multilevel analysis**

Having reviewed some major limitations of classical approaches to the study of social change, we propose an approach which involves modeling time as a socio-historical context of individuals. This approach focuses on strategies for analyzing social change by applying multilevel techniques enhancing the substantive advantages of this approach.

### ***3.1 Adopting the idea of multilevel analysis to the study of social change***

Multilevel analysis is an analytical approach that involves micro units (e.g., individuals) nested within macro units (e.g., schools or countries). We have variables describing individuals and variables describing contexts. This approach allows us to estimate simultaneously the effects of both micro and macro level variables on an individual level outcome. Thus, the aim is to predict values of a dependent variable based on a function of predictor variables at more than one level. In addition, the effects of micro level variables can be expressed as a function of macro level characteristics. The general multilevel model was initially developed in the context of educational studies on the effects of school classes on students' performance (e.g., Willms and Raudenbush 1989; Goldstein 1987).

Our objective is to transfer the school example of hierarchical data structure to our repeated survey case. Though the most important textbooks on multilevel analysis cover a wide range of data types (Goldstein 2011; Hox 2010; Raudenbush and Bryk 2002; Snijders and Bosker 1999; Kreft and De Leeuw 1998), none discusses the repeated cross-section case for studying social change.<sup>5</sup> Hence, multilevel models for repeated surveys are relatively poorly developed and therefore rarely applied.

The criteria for determining the reasonableness of every statistical regression model is provided by theory. Thus, before elaborating how the statistical multilevel models for repeated surveys could look like, we should focus on our underlying theoretical multilevel assumptions. To do so, we turn to an example from the field of social inequality research. Our research question is: Why has the poverty risk of individuals living in families in Germany increased in the past forty years? Since the 1970s, the inequality of income distribution and, consequently also the relative income poverty in West Germany has increased almost continuously. At 14 percent in 2010, the proportion of the relative income poor has increased enormously compared to forty years ago (Grabka and Frick 2010; Groh-Samberg 2010). Over this entire period, families have been one of the main risk groups. In the following sections, we will keep referring to this example.

To explain this increase in family poverty, we refer to Boudon's theory of social change (Boudon 1986, 1983). Contrary to traditional social change theories which stay on the macro level of social structure, Boudon argues that effects of one macro variable on another can be understood only by taking into account the actions of individuals. However,

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<sup>5</sup> Time-related nested models are only developed for panel designs (e.g., growth curve modeling), enabling the study of individual, not social change (e.g., Rabe-Hesketh and Skrondal 2008). Unlike repeated surveys, panel surveys follow the same individuals over time. Thus, using panel data for multilevel analysis usually gives us points in time ( $t$ ) nested within individuals ( $i$ ).

phenomena on the macro level are not seen only as a pure addition of individual actions but as emergent properties. Boudon accounts for this relationship in the multilevel model of sociological explanation (also see Coleman 1994, 1987). Hence, the macro level constitutes a social or socio-historical context in terms of changing material, institutional and cultural conditions. These conditions are linked to the micro level of individuals because each period constitutes a specific social framework for individuals, such as relatively low fertility, low female employment, and comparatively high unemployment. For individuals living in this specific context, these circumstances restrict or facilitate certain courses of action. Therefore, the poverty risk of individuals living in these circumstances should be different than the poverty risk of individuals living in a different year marked by other social conditions.

To incorporate this theoretical multilevel idea into a statistical model, we propose treating individuals of repeated cross-sectional surveys as micro level units and each survey year as a contextual unit, with time-varying macro level conditions as the contextual variables. This enables us to test how the poverty risk of individuals is influenced both by characteristics of individuals themselves (e.g., educational attainment) as well as by characteristics of time interpreted as social context (e.g., changing unemployment rate, changing fertility rate, or changing child benefits). In addition, we want to know if micro level effects have changed over time and, if so, why. But how can we achieve this?

### ***3.2 Recent developments in using multilevel techniques in social change studies***

Although the established textbooks on multilevel analysis do not contain specific approaches to analyzing social change, some efforts have been made to apply multilevel models to the analysis of social processes using repeated cross-sectional data.

To our knowledge, the first proposal for such a model stems from DiPrete and Grusky (1990). They focus on estimation problems that arise in cases in which the contextual units are years, not schools or countries. They stress that the likely serial correlation of the error terms at the year level results in biased estimates of standard errors. To deal with this problem, they develop a mixed estimator or, more precisely, a generalized least-squares (GLS) estimator. DiPrete and Grusky model the change in the effects of race and gender on socioeconomic status as a function of change in macro level variables, applying it to (only) 14 surveys of the GSS.

Firebaugh and Haynie (1997) take up this point, emphasizing the increasing importance of this approach given that repeated surveys (such as the GSS) continue to cumulate data over ever longer periods. The authors also highlight the problem of serial

correlation and criticize the fact that methods are still not well developed for cases with points in time as the macro level units. Firebaugh and Haynie replicate the analysis of DiPrete and Grusky (1990) with the same GSS data using the HLM2 program without adjusting for serial correlation at the year level. Overall, they obtain similar results.<sup>6</sup> Although Firebaugh (2008, 1997) encourages researchers to apply multilevel analysis to the study of social change, he does not elaborate on the models in any detail. We will do so in the next section of this paper.

Yang and Land (Yang 2008; Yang and Land 2008, 2006) also use multilevel models to study social change. They aim to circumvent the identification problem in APC analysis (Chapter 2.1), so they focus on more technical reasons for applying multilevel models. In a series of papers, Yang and Land demonstrate that multilevel modeling can be used to obtain estimates of age, period, and cohort differences in happiness, also using repeated cross-sectional data. In this approach, age is entered at level one, and cohort and year as cross-classified variables at level two (also see O'Brien, Hudson, and Stockard 2008). The cross classified random effect model (CCREM) of Yang and Land has recently been applied in other social change related studies with the aim to disentangle cohort and period effects (e.g., Wilkes and Corrigan-Brown 2011; Lois 2011).

This brief literature review shows that a number of authors have suggested using multilevel models to study social change. However, these models have not been fully developed and are still not included in the standard repertoire of data analysis in social change research.

### **3.3 *Multilevel models with time as context – step by step***

In this section, we show how a social change-related model in which time is interpreted as socio-historical context can be specified. Given the complexity of multilevel models, we do this on a step-by-step basis. First, we state the aim of each model, and then we present its statistical equation. Finally, we illustrate how these models can answer substantive research questions related to social change, which are based on our example of changes in family poverty (Chapter 3.1).

#### *Detecting changes at the micro level: Changing parameter model (fixed effect approach)*

As a first step, before estimating multilevel models, it is useful to detect whether the association of  $X$  and  $Y$  has changed or remained constant over time. In our case, an interesting

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<sup>6</sup> This might be an indicator that serial correlation, in this particular case, is not as severe as assumed. However, in general, serial correlation requires further examination (see Chapter 3.4).

question is: Has the effect of education on individuals' poverty risk changed from the 1970s to the present? This question can be examined by applying the changing parameter model to our repeated cross-sectional data (Chapter 2.2). As we have seen, we include dummy variables for the different points in time and interact them with the individual level explanatory variables of interest (fixed effect approach). This method proves to be rather inelegant if we have a survey with, say, 30 waves, because we have to include main and interaction effects for 29 dummy variables (30 minus the reference year) to the individual level equations. If we had to test three predictors for varying effects, we would have 87 regression coefficients to examine. However, this is a good strategy for obtaining an initial answer to the question of whether or not effects have remained constant over time (Firebaugh 2008; Firebaugh and Haynie 1997). Depending on the nature of the response, the interaction models can be estimated using simple OLS or maximum likelihood estimation. Nevertheless, this approach remains descriptive.

*Explaining changes of parameters: Multilevel models with time as context  
(random effect approach)*

To test hypotheses about the possible causes of the observed change, we propose treating individuals as micro level units and each survey year as a contextual unit with time-varying macro level conditions as the contextual variables. Our focus here will be on the question: What are the macro changes over time that affect the  $X$ - $Y$  relationship?

However, this approach is only applicable if we have a specific number of macro level units, in our case, years. Otherwise, we are faced with the so-called "small N bias": If the number of context units is small but the number of individual units is large, the context effects will likely be overestimated and the standard errors underestimated. Thus, estimates of variance components are biased. To be on the safe side, a rule of thumb among scholars is to use a figure of at least 30 units, given that different authors give different recommendations (e.g., Hox 2010: 234, 235).

In the past, this feature limited the utility of a multilevel strategy for analyzing repeated cross-sectional data, because most survey series did not have enough waves to support reliable estimation of macro level effects (Firebaugh and Haynie 1997: 153). However, the multilevel approach should become increasingly appropriate as repeated surveys continue to cumulate (e.g., there are currently 28 waves of the GSS and more waves are being added every year).

*Step 1: Null model without predictors: Does time matter?*

Compared to OLS regression in multilevel analysis, it is very useful, even necessary, to fit a model with no predictors, the so-called null model or empty model. The key function of this model is to provide information on whether the phenomenon under study varies between the macro level units. The empty model also serves as a benchmark with which other models are compared. Since this model without predictors is equivalent to a one-way analysis of variance with random effects, it is also called ANOVA model (e.g., Raudenbush and Bryk 2002: 69).

Because we assume that we have clustered data— e.g., individuals in 30 years — we would actually have to fit 30 intercepts, one for each year (fixed effects model). Instead, multilevel analysis uses only two parameters:

$\beta_0$  is an average intercept – the mean of the intercepts, the “grand mean”, and  
 $u_{0t}$  its residual variance across years – the variation of the intercepts,  
plus an error term for the individual level ( $e_{it}$ ), as in OLS regression. Thus, the equation for the null model without predictors is:

$$Y_{it} = \beta_0 + u_{0t} + e_{it} \quad (5)$$

where “ $i$ ” indexes individual and “ $t$ ” indexes year.

In all following equations, residuals at both levels are assumed to follow normal distributions with zero means:  $e_{it} \sim N(0, \sigma_e^2)$  and  $u_{0t} \sim N(0, \sigma_{u_0}^2)$ . The two random terms and their variance include substantive information:  $u_{0t}$  is the ‘between year variation’ and  $e_{it}$  the ‘between individual within year variation’. The variance estimates of the random terms from this model are also used to calculate the *intraclass correlation*  $\rho$ .<sup>7</sup> In our case,  $\rho$  is the proportion of the total variance that is at the year level. It varies between 0 and 1:

$$\rho = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_e^2} \quad (6)$$

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<sup>7</sup> There is a difference in how the measure intraclass correlation  $\rho$  in simple null models is labelled. In most multilevel books, the measure is called the “intraclass correlation coefficient” (ICC) (e.g., Raudenbush and Bryk 2002: 24), but some speak of the “variance partitioning coefficient” (VPC) (primarily the Centre for Multilevel Modelling at the University of Bristol in its training manuals, e.g., Steele 2008: 8). In a simple null model like this, the VPC is equal to the ICC. However, the calculation of the ICC in more complex models means the degree of dependence among observations within the same group or, in other words, the correlation between the  $Y$ -values of randomly selected individuals from the same group (Raudenbush and Bryk 2002: 75; see also Snijders and Bosker 1999: 16 f., Kreft and De Leeuw 1998).

It is necessary to calculate  $\rho$  before performing a multilevel analysis with predictors; from a statistical point of view, we use multilevel models only if we have clustered data. It is likely that individuals within a year share the same socio-structural environment and, thus, are similar (compared to individuals from other years). Hence, we assume dependencies in our data. If we were to analyze dependent data with single level models (e.g., OLS regression) and ignore the clustered data structure, we would obtain biased standard errors and consequently biased inference tests. Thus, we would have an increased risk of finding relationships and differences where none exist (e.g., Hox 2010: 4f.; Duncan, Jones, and Moon 1998). In multilevel analysis, we explicitly model these dependencies between the cases and can even estimate the degree of clustering by the intraclass correlation.  $\rho$  is a measure for showing us if we do, in fact, have dependencies in our data and, thus, whether multilevel analysis is indeed the appropriate method. For example, if  $\rho=0.01$ , i.e., only 1 percent of the total variance is at the year level, a multilevel approach is certainly not worth the effort, and fitting a single level model is more useful. However, there is no rule of thumb for the minimum value of  $\rho$ .

Besides this statistical measure, we also get substantive information with  $\rho$ , namely: How much of the variance of  $Y$  (e.g., poverty) is at the year level? For our specific repeated cross-section case, this means that the more the poverty risk of individuals living in families within a year is alike (as compared to individuals from other years), the more likely it is that the causes of poverty are related to time or, respectively, to changing macro processes.

*Research questions related to social change that this model can answer:*

- a) Are individuals within the same year statistically related? Does time matter?
- b) What proportion of the total variation in  $Y$  can be attributed to time? (cf. ICC)

*Example: Explaining trends in family poverty in Germany, 1970-2010*

- a) Does time matter with respect to the individual poverty risk?
- b) To what extent is family poverty determined by time-varying macro processes and to what extent by individual characteristics?

*Step 2: Random intercept model: Which individual variables and which time-varying contextual variables explain  $Y$ ?*

If time does matter, it is useful to continue with a random intercept model. Now we are interested in the question: What determines  $Y$ ? Aside from studying the effects of individual level characteristics, we want to know which changing macro characteristics influence our



response variable. This model is called the ‘random intercept model’, because only the intercept is allowed to vary between the years. The central assumption is that the effect of the explanatory variables is the same every year.

(1) It is useful and common to start with a random intercept model that includes only *individual level explanatory variables*  $X_{it}$ , e.g., educational attainment (e.g., Hox 2010: 56, 57). In multilevel analysis, it is useful to center the metric explanatory variables  $X$  for both interpretation and statistical reasons (Algina and Swaminathan 2011; Hox 2010:59f.). The interpretation is the same as in simple regression. However, we take account of the hierarchical data structure, i.e., the fact that individuals in the same year are related.

In order to attain a clearer understanding, we first explicate separate equations for each level and then combine them into a single equation model. In the micro model, we have a separate regression equation for each year  $t$ . In other words, we specify the ‘within year’ part of the model:<sup>8</sup>

$$Y_{it} = \beta_{0t} + \beta_1 X_{it} + e_{it} \quad (7)$$

In the macro model, we specify the ‘between year’ part of the model. The parameter of the ‘within year’ model becomes the response. Thus, the time-specific intercept is elaborated as:

$$\beta_{0t} = \beta_0 + u_{0t} \quad (8)$$

If equation (8) is inserted into equation (7), we obtain the single equation form of the random intercept model:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + u_{0t} + e_{it} \quad (9)$$

In the random part of the combined model (8), we have the two random terms, as in the null model, i.e.,  $u_{0t}$  (‘between year variation’) and  $e_{it}$  (‘within year variation’). Again, as in the previous ANOVA model, we are primarily interested in estimating their variances:

$\sigma_{u_0}^2$  the ‘between year variance’ after controlling for the explanatory variables, and

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<sup>8</sup> To keep the models simple, we introduce only one predictor variable at each level. Extending the model to include more variables is straightforward.

$\sigma_e^2$  the ‘between individual within year variance’ after controlling for the explanatory variables.

On the basis of the two variances, we again estimate the intraclass correlation  $\rho$  and ask: How much variance of  $Y$  is at the year level when we control for differences in the composition of the population with respect to  $X$  at each point in time? It is important to note that, in contrast to simple regression models, in multilevel models, the error terms and their variance (random part) are equally informative and, thus, interpreted as the parameters in the fixed part.

In the fixed part of the equation, we estimate the coefficients  $\beta_0$  and  $\beta_1$ :

$\beta_0$  is once again the grand mean, the average intercept of the year level, and

$\beta_1$  is, as in simple regression, the slope of  $X$ .

(2) Then, as a conceptual extension of the standard approaches to studying social change (see Chapter 2), we add *time-varying macro level variables*  $Z_t$  to the model, e.g., the unemployment rate.<sup>9</sup> As we will see, the addition of  $Z$ -variables allows us to explain the intercept differences between the years.

Again, let us first specify the ‘within year’ part of the model: It is the same equation as in the random intercept micro model with only individual level variables (see equation 7):

$$Y_{it} = \beta_{0t} + \beta_1 X_{it} + e_{it} \quad (10)$$

Again, in the macro model, the intercept of the micro model becomes the response variable. Now we explain intercept differences between years with our time-varying macro variable  $Z_t$ :

$$\beta_{0t} = \beta_0 + \alpha_1 Z_{1t} + u_{0t} \quad (11)$$

Residuals at both levels are again assumed to follow normal distributions with zero means:  $e_{it} \sim N(0, \sigma_e^2)$  and  $u_{0t} \sim N(0, \sigma_{u_0}^2)$ , and years and individuals are assumed to be independent  $Cov[u_{0t}, e_{it}] = 0$ . If we substitute (11) into (10), we get the combined model:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \alpha_1 Z_{1t} + u_{0t} + e_{it} \quad (12)$$

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<sup>9</sup> The macro data can either be aggregated from the micro level data (e.g., median income, unemployment rate) or global indicators from external data sources can be included (e.g., GDP per capita).

This step is a crucial substantive advantage of using multilevel models to understand and explain social change. As we have seen, this was not possible with the standard models (see Chapter 2). Further, we can define which proportion of the initial level 1 and level 2 variance is explained by  $X$  resp.  $Z$ .

*Research questions related to social change that this model can answer:*

- a) What proportion of ‘between year variation’ is due to different population compositions with respect to the individual level variables?
- b) How does the time-varying macro variable  $Z$  influence  $Y$ , and to what extent can we explain the ‘between year variation’ of  $Y$ ?

*Example: Explaining trends in family poverty in Germany, 1970-2010*

- a) What proportion of the variation in poverty over time can be accounted for by differences in individual characteristics, e.g., different educational levels?
- b) How do different child benefit packages affect the poverty risk of individuals living in families? And what proportion of the total ‘between year variation’ in poverty can be attributed to child benefits?

*Step 3: Random slope model: Does the effect of  $X$  on  $Y$  change over time?*

The central assumption of the random intercept model just presented is that, in every year, the effect of the explanatory variable (e.g., educational attainment) is the same, and thus, when visualizing it, each year line has the same slope. However, in some cases, our theory might lead us to assume that the effect of the explanatory variable differs over time, e.g., the effect of educational attainment on poverty risk could have become stronger from the 1970s to 2010 because individual attainment has become an increasingly important prerequisite for the individual welfare position throughout the years.<sup>10</sup> But how can we translate this theoretical assumption into a multilevel model? Looking at the combined model equation (15), we can achieve this by adding a random term to the slope of  $X$ . The regression equation at the micro level is almost identical to the one in the previous model; note, however, that now the slope of  $X$  ( $\beta_{1t}$ ) has the subscript  $t$ , indicating that the slope can vary over time:

$$Y_{it} = \beta_{0t} + \beta_{1t}X_{1it} + e_{it} \quad (13)$$

<sup>10</sup>Theoretically, it is possible to put a random slope on one, several or even all the explanatory variables. However, depending on the number of years in our data set, in practice, we often might not have enough power to put a random slope on more than one explanatory variable.

Again, in the macro model, the parameters of the micro level become the response variables. But in contrast to the fixed effect model, we now assume that not only the intercept ( $\beta_{0t}$ ) but also the slope ( $\beta_{1t}$ ) varies over time:

$$\begin{aligned}\beta_{0t} &= \beta_0 + \alpha_1 Z_{1t} + u_{0t} \\ \beta_{1t} &= \beta_1 + u_{1t}\end{aligned}\tag{14}$$

Substituting the equations, we arrive at the combined random slope model:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \alpha_1 Z_{1t} + u_{0t} + u_{1t} X_{1it} + e_{it}\tag{15}$$

In the fixed part of the single equation, we have the parameter  $\beta_0$ ,  $\beta_1$ , and  $\alpha_1$ . In the random part, we have – besides the error term for the intercept of level 2 ( $u_{0t}$ ) – an additional error term for the variation of the coefficients of  $X$  between years ( $u_{1t}$ ), and the error term of the individual level ( $e_{it}$ ). Again, it is important to note that, in multilevel models, the residual variation (random part) is as informative as the parameters in the fixed part of the model:

$u_{0t}$  is again the variation between years;

$u_{1t}$  is the variation between years of the slopes of  $X$ ;

$e_{it}$  is as before the variation between individuals within years.

Residuals at both levels are again assumed to follow normal distributions with zero means:

$e_{it} \sim N(0, \sigma_e^2)$  and  $u_{0t} \sim N(0, \sigma_{u_0}^2)$  and  $u_{1t} \sim N(0, \sigma_{u_1}^2)$ . However, now intercepts and slopes at the year level are not independent, i.e., we have a covariance between intercepts and slopes ( $\sigma_{u_0 u_1}$ ) that also has to be interpreted.

Thus, we have two more random parameters in the random part of the model than we did in the random intercept model. In addition, we estimate  $\sigma_{u_1}^2$  and  $\sigma_{u_0 u_1}$ :

$\sigma_e^2$  is the ‘between individual within year variance’ after controlling for the explanatory variables resp. conditional on educational achievement;

$\sigma_{u_0}^2$  is the variance in intercepts between the years;

$\sigma_{u_1}^2$  is the variance in slopes between years;

$\sigma_{u_0 u_1}$  is the covariance between intercepts ( $u_{0t}$ ) and slopes ( $u_{1t}$ ).

The covariance between intercepts and slopes may have 3 possibilities or patterns:

- (a) A positive value of  $\sigma_{u_0u_1}$  implies a pattern of positive correlation of slopes and intercepts. In years with higher (expected) levels of  $Y$ , the effect of  $X$  on  $Y$  tends to be stronger. If we plot the micro model for each year, this would result in a pattern of regression lines fanning out for each year. In relation to our example, this result could mean that the effect of education on poverty would tend to be stronger in years with higher poverty risks (larger intercepts).
- (b) If  $\sigma_{u_0u_1}$  is negative, this implies that there is an inverse (negative) relationship between intercepts and slopes (e.g., higher intercepts tend to go together with shallower slopes). If we again imagine plotting the different micro level models, we find a pattern of converging regression lines per year. In the context of our example, a negative covariance of random intercept and random slope leads us to the conclusion that the protective effect of education is weaker when poverty levels are high.
- (c)  $\sigma_{u_0u_1} = 0$  indicates that there is no (monotone) relationship between the random intercept and random slope.

If we consider the residual variance at the year level, we are faced with a slightly more complicated situation:

$$\begin{aligned} \text{Var}(u_{0t} + u_{1t} x_{1it}) &= \text{Var}(u_{0t}) + 2\text{Cov}(u_{0t}, u_{1t} x_{1it}) + \text{Var}(u_{1t} x_{1it}) & (16) \\ &= \sigma_{u_0}^2 + 2\sigma_{u_0u_1} x_{1it} + \sigma_{u_1}^2 x_{1it}^2 \end{aligned}$$

The total residual variance in a random slopes model is  $\sigma_{u_0}^2 + 2\sigma_{u_0u_1} x_{1it} + \sigma_{u_1}^2 x_{1it}^2 + \sigma_e^2$ .

On this basis, the intraclass correlation  $\rho$  is again estimated in order to obtain information on the explained variance at both levels. It is still calculated by year level variance divided by total variance.

In random slope models, it is useful, and even necessary, to center the metric explanatory variables  $X$  both for interpretation and for statistical reasons:  $\beta_0$ , and also  $u_{0t}$  depend on where we place  $X=0$ . Thus, the variance  $\sigma_{u_0}^2$  is also affected, as well as the covariance  $\sigma_{u_0u_1}$  (Algina and Swaminathan 2011; Hox 2010: 59f.).

*Research questions related to social change that this model can answer:*

- a) Does the effect of  $X$  on  $Y$  change over time?
- b) Are changes in the effects of  $X$  on  $Y$  related to the time-specific average value of  $Y$  (covariance between intercept and slope)?

*Example: Explaining trends in family poverty in Germany, 1970-2010*

- a) Does the effect of education on poverty increase or decrease over time?
- b) Is the effect size of education related to the poverty level in each year?

*Step 4: Random slope model with cross-level interaction: How can we explain the changing effects of  $X$  on  $Y$ ?*

As in simple regression, we can include interaction effects in our models and thereby model the idea that the effect of one explanatory variable on  $Y$  depends on the value of another explanatory variable. In multilevel models, an interaction between an individual level variable and a context level variable is called a cross-level interaction. Now, in our final model, we add a cross-level interaction between an explanatory individual level variable that had a random slope in the previous model and a time-dependent contextual variable (Hox 2010: 58). This random slope model including cross-level interactions is also called the full model, because it includes all possible effects and, thus, is the most informative model. In this final model, the micro level coefficients are themselves expressed as a function of macro characteristics that change over time. Hence, as Boudon and Coleman recommend, we model individual action against the background of the changing social context (Chapter 3.1). This is a considerable increase in information we can obtain to understand social change compared to our standard approaches (Chapter 2). With the changing parameter model, we could only detect, but not explain, time-varying effects (Chapter 2.2). With the full model, it is possible to explain why  $X$ -variables change their effects on  $Y$  over time.

The regression equation at the micro level is identical to the one in the previous random slope model (see equation 13). Note that again, the slope for  $X$  ( $\beta_{1t}$ ) has the subscript  $t$  indicating that the slope can vary over time:

$$Y_{it} = \beta_{0t} + \beta_{1t}X_{1it} + e_{it} \quad (17)$$

As before, in the macro model, the parameters of the micro level become the response variables. Again we assume that both the intercept ( $\beta_{0t}$ ) and the slope ( $\beta_{1t}$ ) vary over time. However, now, in contrast to the random slope model (see equation 14), the time-varying

slope of  $X$  ( $\beta_{1t}$ ) is also a function of the explanatory macro variable  $Z$ . Thus, we explain a change in the  $X$  parameter by the social context defined by time:

$$\beta_{0t} = \beta_0 + \alpha_1 Z_{1t} + u_{0t} \quad (18)$$

$$\beta_{1t} = \beta_1 + \alpha_2 Z_{1t} + u_{1t}$$

Substituting (18) into (17) the equation results in a cross-level interaction:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \alpha_1 Z_{1t} + \alpha_2 X_{1it} Z_{1t} + u_{0t} + u_{1t} X_{1it} + e_{it} \quad (19)$$

In the fixed part of the full model, we have the parameters  $\beta_0$ ,  $\beta_1$ , and  $\alpha_1$  plus an additional parameter  $\alpha_2$  for the cross-level interaction of  $X$  and  $Z$ . In the random part, as in the combined random slope model (see equation 15), we have the error term for the intercept of level 2 ( $u_{0t}$ ), the error term for the variation of the coefficients of  $X$  between the years ( $u_{1t}$ ), and the error term of the individual level ( $e_{it}$ ).

*Research questions related to social change that this model can answer:*

- a) How can the slope difference of  $X$  between years be explained? Which time-varying macro indicators explain the changing effects?
- b) What are the macro changes over time that affect the  $X$ - $Y$  relationship?
- c) Compared to the null model, what proportion of the variance at the micro and the macro level can we explain with the full model?

*Example: Explaining trends in family poverty in Germany, 1970-2010*

- a) Which contextual variables explain ‘between year’ differences in the effect of education on poverty risk? For instance, can a high unemployment rate explain the differences in the effect size of education on poverty?
- b) Which time specific contextual factors moderate the effect of education on one’s poverty risk?
- c) Compared to the null model, what proportion of the variation in poverty over time can be accounted for by differences in individual characteristics, e.g., different educational levels?

### 3.4 *Problems of the approach*

We have shown that studying social change with multilevel techniques presents substantial and methodological advantages compared to standard approaches. First, it allows us to interpret individual action against the background of a socio-historical context. Second, multilevel analysis takes into account the fact that individuals living in the same year tend to be more similar to each other than individuals living in different years. If we were to analyze dependent data with single level models and thus ignore the clustered data structure, we would obtain biased standard errors and incorrect estimates of precision. Additionally, in contrast to all standard approaches, micro and macro explanatory variables are analyzed simultaneously. As an extension to the changing parameter model, multilevel models can be also used to study the causes of a changing parameter (e.g., varying slope), since the  $X$ - $Y$  relationship is modeled as a function of change in macro level conditions.

However, the approach does involve some statistical problems. Most of these complications relate to the temporal ordering of our multilevel data. For example, we must take into account that the data for 1970 immediately precedes the data for 1971 and that one year can affect subsequent years (but not preceding ones). At this point, we must deal with similar issues and are faced with comparable problems as time series applications. Thus, the possible solutions we discuss are guided mainly by approaches of time series research.<sup>11</sup>

#### *Serial correlation*

In our case, in which the higher level units consist of years, we have a likely serial correlation, or autocorrelation of errors at the macro level, resulting in biased estimates of standard errors: The error term  $u_t$  at year  $t$  tends to be positively correlated with the error terms  $u_{t+1}$ ,  $u_{t+2}$ , ... and  $u_{t-1}$ ,  $u_{t-2}$ , ... and so on.<sup>12</sup> This violates the Gauss-Markov assumption of the absence of serial correlation ( $\text{CORR}(u_t, u_{t-1}) = 0$ ) (Wooldridge 2009: 349). Such correlation in the error terms usually arises from the correlation of the omitted variables that the error term captures. Thus, the values of the variable  $Z_t$  tend to be positively correlated with the values of  $Z_{t-1}$

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<sup>11</sup> According to time series analysis, as a first step, we have to test our macro processes under study very precisely and identify whether we have *stochastic* or *deterministic* and *stationary* or *nonstationary* processes (Chatfield 1989: 27 et seq.; Wooldridge 2009: 378). The goal, according to most time series textbooks, is to achieve stochastic stationary models as most of the probability theory of time series is concerned with it (e.g. Box, Jenkins, and Reinsel 2008; Enders 2004: 48 et seq.). While most economic time series (e.g. unemployment rate or GDP) are assumed to be stochastic, in most cases, it is necessary to turn a nonstationary series into a stationary one (with constant mean and variance).

<sup>12</sup> If errors in one year (e.g., 1973,  $u_{1973}$ ) are correlated directly with errors in the previous year ( $u_{1972}$ ), the correlation is called a first-order autocorrelation and occurs most commonly in social science analyses. However, the correlation might not take place until after two, three, or four years, which would be higher order serial correlation (Maddala and Lahiri 2009: 240).



(Maddala and Lahiri 2009: 240). For example, if the female activity rate or the unemployment rate is comparatively low in 1972, then it is likely to be similarly low in 1973 (Table 1).

Table 1 Partial listing of data on West German female activity and unemployment rates, 1972-2010

Year	Female activity rate	Unemployment Rate
1972	47.6	1.1
1973	48.4	1.2
1974	48.3	2.6
...	...	...
2008	68.3	7.2
2009	68.9	7.7
2010	69.4	7.4

Source: Female activity rate: Results of the German Microcensus, published by the Federal Bureau of Statistics; Unemployment rate: Statistics of the Federal Employment Agency.

To detect the presence of first-order autocorrelation, the simplest and most popular test is the Durbin-Watson test.<sup>13</sup> The test is implemented in most statistical programs and involves the calculation of a test-statistic based on the residuals from the OLS regression procedure. Its coefficient  $d$  is interpreted as the measure of first-order autocorrelation between two errors. Tables exist to test the hypothesis of zero autocorrelation against the hypothesis of first-order positive autocorrelation (e.g., Pindyck and Rubinfeld 1998: 165; Maddala and Lahiri 2009: 616). A rule of thumb holds that if the value of  $d$  is close to 0 or 4, the errors are highly correlated (Maddala and Lahiri 2009: 240).<sup>14</sup> Other tests are based on the autocorrelation coefficient  $\rho$ .  $\rho$  measures the correlation between errors in year  $t$  and errors in year  $t-1$ . When  $\rho=0$ , no first-order serial correlation is present, while a large value of  $\rho$  implies the existence of one (Pindyck and Rubinfeld 1998: 161).

If the Durbin-Watson test or the autocorrelation coefficient suggest serial correlation, several solutions exist for stationary processes (with constant mean and variance), which we also see in time series analysis (e.g., Engelhardt 2004: 378). The most common way is to use a first-difference equation (Maddala and Lahiri 2009: 242; Wooldridge 2002: 279-284). Here we regress  $(Y_t - Y_{t-1})$  on  $(Z_t - Z_{t-1})$ . Of course, in differencing, we lose the first year for each

<sup>13</sup> There are also several tests for higher order serial correlation, which we will not cover in this paper (see Wooldridge 2009: 417-419).

<sup>14</sup> The expected value of  $d$  in a situation of no autocorrelation is 2.

cross-section, and it is applicable only for linear trends. The implicit assumption is that the first differences of the errors ( $u_t - u_{t-1}$ ) are independent. The first-difference (FD) model would look like:<sup>15</sup>

$$\Delta Y_t = \alpha + \beta \Delta Z_t + \Delta u_t \quad (20)$$

However, attention should be paid to the fact that the interpretation of the coefficients is now different than estimating absolute macro level effects. We now explain changes by changes, e.g., explaining increased poverty rates by declined fertility rates. How far this method makes sense depends on one's particular research question.

In stochastic trends which are widespread in economic time series (such as unemployment rate or GDP), autocorrelation is often corrected by estimating models in which the error terms are autoregressive (e.g., by Cochrane-Orcutt estimation) (for further details, see Maddala and Lahiri 2009: 246-249 and Box, Jenkins, and Reinsel 2008: 55 et seq.). If the error  $u_t$  is regressed on  $u_{t-1}$ , it is called a first-order autoregression or AR(1) because  $u_t$  is regressed on its past with only one lag. In time-series cross-section models (Chapter 2.3), the serial correlation problem of stochastic processes is mostly tackled by the Beck and Katz method, which involves adding lagged dependent variables (LDV) to the model and using panel-corrected standard errors (PCSE) (Beck and Katz 1995, 1996). However, it should make theoretical sense again to explain  $Y$  with  $Y_{t-1}$ , which will not always be the case.

### *Small N problem*

Another problem of adopting the multilevel approach to repeated surveys is the so-called “small N problem”, which implies biased estimates in cases of a small number of contextual level units, years in our case. If the number of years is small but the number of individuals large, which normally will be the case in repeated cross-sections, it is likely that we will overestimate the effects of the socio-historical context and underestimate standard errors. However, this problem occurs in most multilevel structures. A solution is to use more sophisticated estimation methods, such as the Bayesian-inspired Markov Chain Monte Carlo (MCMC) estimation (Gill 2008; Lynch 2007). The basic idea of this approach is to estimate the parameters of interest from the distribution in the sample. Unlike the frequentist maximum likelihood estimation resting on multivariate normality assumptions, MCMC methods are simulation-based procedures and run for many iterations. At each iteration, an estimate for

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<sup>15</sup> The extension of this model to multiple independent variables is straightforward.

each unknown parameter is produced (Browne 2012: 3).<sup>16</sup> MCMC is now the preferred form of estimation for complex multilevel models (though not without introducing some new challenges of its own): Most textbooks on multilevel analysis include a chapter on Bayesian analysis encouraging social scientists to apply the approach (e.g., Goldstein 2011: 45 et seq.; Hamaker and Klugkist 2011; Draper 2008). Consequently, several popular statistical packages include the option of Bayesian analysis at this time (e.g., MLWin, MPLus (since version 6), R, and SAS).

#### *No random sample at the year level*

A final problem we would like to point out is that the contextual units we use, years, are not drawn at random (this is the case for individuals at level 1). However, for the substantially relevant period, we analyze data from every year not just a subsample of years. In our example, we focus on the increase of family poverty since the 1970s (Chapter 3.1), so we are only interested in the period of 1970 to 2010. Our aim is to describe social change in precisely this period. We do not intend to draw inferences to other periods of time (e.g., to the Middle Ages or the future). Therefore, we apply methods of inferential statistics only in a heuristic sense. In cross-national research in which scholars must deal with similar issues, the problem is widely ignored. The issue has been discussed only recently (e.g., Beckers 2011). Possible solutions might also be found by using Bayesian estimation methods.

Altogether, the complications that might occur emphasize that the presented analysis strategy can be assumed to be more complicated than current approaches to the study of social change, as well as regular multilevel analysis. However, in our view, the substantial advantages of treating time as socio-historical context justify the application and make it rewarding.

## **4 Discussion and Conclusion**

Repeated cross-sectional surveys will become increasingly appropriate for multilevel models of social change as they continue to cumulate. We argue that applying multilevel techniques to these data offers theoretical and methodological advantages. Our paper makes two main contributions. First, we hypothesize and elaborate on our assumption that the current approaches to the study of social change have substantive shortcomings, specifically for theory-driven analyses. Second and primarily, we focus on how to analyze social change using multilevel techniques. We do not develop new methods, but rather applying existing

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<sup>16</sup> For more details about MCMC methodology see, for example, Gilks, Richardson, and Spiegelhalter 1996.

models within a different conceptual framework to demonstrate that the approach is fruitful and can be a useful tool in social change research.

In theoretical terms, we conceptualize time as a socio-historical context for individuals. For example, the poverty risk of individuals living in a specific social environment (e.g., with high unemployment, low female employment, or low child care) should be affected by these socio-historic conditions, in addition to individual characteristics (e.g., education or gender). Our proposal for incorporating this theoretical multilevel idea into a statistical model is to treat individuals of repeated cross-sectional surveys as micro level units and each survey year as a contextual unit with time-varying macro level conditions as the contextual variables.

Given the complexity of the multilevel approach, we consider it necessary to spell out the procedure on a step-by-step or, more precisely, on a model-by-model basis. Doing so required a relatively technical description of the procedure. Therefore, this concluding section offers a summary of the benefits of the multilevel strategy for the study of time-dependent social processes: First, in multilevel analysis, we take into account the clustered data structure and, thus, control for the dependencies of individuals living in the same year. Second, in contrast to all standard approaches, both variable groups that we regard in sociological terms as equally meaningful are considered – both micro and macro explanatory variables. Moreover, multilevel modeling is not only a means of assessing the relative contribution of individual and contextual effects but also provides a way to frame and test ideas about time-related processes and variability. Third, as an extension of the changing parameter model, multilevel models can be used to study the causes of a changing parameter. For example, we can detect which contextual variables explain between-year differences in the effect of education on one's poverty risk.

However, there are also a number of obstacles that have to be overcome with this approach. The key problem is serial correlation. Since this is likely to be a problem of time series applications in general, we present possible solutions guided by tools of time series research. Whether these approaches can be adapted successfully to a multilevel context needs to be further explored.

Moreover, it remains to be seen under which conditions our approach can be applied using panel data. Although we argue that repeated cross-sectional data are best suited for the study of social change (Firebaugh 2008: 172 et seq.), applying these models to panel data might also be advantageous. For example, intra-individual changes can be analyzed more properly with panel surveys than with repeated cross-sections. Although most panel studies

(e.g., the GSOEP) were not generated until the early 1980s and initially conducted to study individual change over the life course, they are increasingly used to observe long-term social processes as well. Whether our approach using each wave as a contextual unit could be a fruitful supplement or whether the additional panel structure will cause further complications (attrition is a major problem but also serial correlation) needs to be tested in future.

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