Explaining Social Change:
The Application of Multilevel Models to Repeated Cross-Sectional Survey Data

Malcolm Fairbrother
Lecturer
School of Geographical Sciences
University of Bristol

m.fairbrother@bristol.ac.uk

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Abstract:
Social scientists make regular use of multilevel models in analyzing data on survey respondents located in many different countries or sub-national jurisdictions. Growing numbers of these datasets span multiple waves, and researchers are beginning to confront the question of how to incorporate this longitudinal dimension into their studies. Simultaneously comparative and longitudinal models should produce many valuable new insights, particularly about the drivers of political and social change broadly defined; but they will only do so if they are specified appropriately. This paper identifies potential problems and limitations in existing analyses, and proposes extensions of existing multilevel modeling techniques that should help put comparative longitudinal survey data to better use. These extensions help to distinguish between longitudinal and cross-sectional relationships, and allow change over time in y to be a function of change over time in x and/or the time-invariant level of x. The paper concludes with an application to the study of why religiosity has declined (or secularism expanded) in some countries and not others.
1 Introduction

In the last decade, multilevel regression models have become a normal tool for social scientists, and particularly for social scientists analyzing survey data. Multilevel models, also known as mixed, random effects, or hierarchical linear models, are useful for analyzing data which are in some sense grouped or clustered (for overviews see e.g., Gelman and Hill 2007; Steenbergen and Jones 2002). The growing popularity of multilevel models has been due in large part to their usefulness for analyzing specifically comparative survey data. Such data consist of observations on individual survey respondents who are drawn from, and can therefore be treated as clustered within, many different countries or sub-national jurisdictions such as regions, states, or provinces. For convenience, this paper will refer to countries, but the same principles apply to sub-national jurisdictions.

Multilevel models applied to comparative survey data combine the strengths and capacities of micro- and macro-level research, insofar as they examine two core units of analysis simultaneously: individual people, on the one hand, and the societies or polities of which they are members, on the other. Such models illuminate differences among nations, and exploit national differences in testing theories about the consequences of macro-social conditions for individual people’s attitudes, beliefs, circumstances, and behaviors. In other words, multilevel models help to clarify how individuals differ depending on their social and political contexts.

Education researchers were the first social scientists to make extensive use of multilevel models (see e.g., Burstein 1980; Goldstein 1987), but subsequently—and especially once the scope for applications to comparative survey data became clear—geographers (Jones 1991), sociologists (DiPrete and Forristal 1994), epidemiologists (Diez-Roux 1998), and political scientists (Steenbergen and Jones 2002) all became routine users.1 Recent applications of multilevel models to cross-national survey data have examined and sought to identify the covariates of outcomes like union membership (Martin and Brady 2007), political engagement (Solt 2008), concern about the natural environment (Franzen and Meyer 2010), religiosity (Ruiter and van Tubenberg 2009), health (Jen, Jones, and Johnston 2009), voting (Anderson 2006), political attitudes (Barone et al. 2007; Jamal and Nooruddin 2010), poverty (Brady, Fullerton, and Cross 2009), and gender gaps in household labor (Iversen and Rosenbluth 2006). This diversity of applications demonstrates the broad appeal of the method.2

This paper addresses the question of how to apply multilevel models to survey data that are not just comparative, but also longitudinal: repeated cross-sectional data, where each cross-section includes a new sample of respondents drawn from a consistent set of higher-level units, such as countries. Researchers have access to increasing numbers of datasets of this kind, and a small number of studies have already made use of multiple waves of data from one or more cross-national surveys fielded multiple times. Yet in some cases, as this paper will show, the approach adopted by these studies will be misleading and suffer from important limitations. This paper describes superior techniques for analyzing comparative longitudinal survey datasets, which do not suffer from these limitations. The proposed new techniques are only incremental extensions of existing methods, but taken together they are powerful and substantially more informative. Comparative longitudinal survey data should be an invaluable resource particularly for research on

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1 Political science adopted multilevel modelling relatively late. From the perspective of political science, Steenbergen and Jones noted as recently as 2002 that “statistical methods to exploit the information found in multilevel data structures have not been widely used” (218).

2 Not to mention the range of applications in the natural sciences—botany, zoology, genetics, etc.
social change, in the broadest sense; properly specified models should therefore help to answer big questions about why and how societies change, and why some change faster than others. Because of the increasing availability of these kinds of longitudinal comparative survey datasets, the usefulness of the techniques described here should only increase over time.

The first extension is a simple technique for distinguishing between cross-sectional and longitudinal effects when investigating the influence of a time-varying macro-level variable. The second is the application of “growth curves”—a multilevel modeling technique previously used only with data on individuals—to the level of whole societies.

The next section reviews reasons for adding a longitudinal dimension, where possible, to multilevel models of comparative survey data. The third section then discusses the question of how to characterize longitudinal comparative survey data. The fourth section reviews existing multilevel analyses of repeated cross-sectional survey data, noting the approach they have taken and the limitations of such an approach. The fifth and sixth sections describe how two extensions of existing techniques can contribute to more informative analyses of longitudinal comparative survey data, and even the avoidance of highly misleading inferences. The seventh section provides a brief application to the study of why religiosity has declined (or secularism expanded) in some countries and not others. The eighth section concludes.

2 The Promise of Extending Multilevel Models Longitudinally

Multilevel models are a powerful tool for analyzing, and deriving inferences from, comparative survey data about the macro-level determinants of individual-level outcomes. However, most existing studies using multilevel models rely exclusively on cross-sectional comparisons, sometimes with few degrees of freedom at the higher level. The core comparisons in such studies often apply to the higher-level units (e.g., countries), of which there are sometimes fewer than 20 (e.g., Anderson and Tverdova 2003; Brady, Fullerton, and Cross 2009; Iversen and Rosenbluth 2006; Mattes and Bratton 2007; Steenbergen and Jones 2002; Weldon 2006). With so few units, the results of cross-sectional comparisons will often be sensitive to small changes in the set of higher-level units included in the analysis. The results of such studies need to be treated with caution.3

Adding a longitudinal dimension to such work should be methodologically constructive. If a given independent variable is cross-sectionally associated with an outcome of interest, checking for the presence of the same relationship longitudinally is a logical next step in validating the hypothesis that the variable genuinely exercises some influence over the outcome in question—that the relationship is not spurious, or would disappear with additional controls.

Aside from subjecting existing results and theories to further empirical testing or validation, where change over time is not in itself a central concern, longitudinal research is also a direct way of studying social change, in the broadest sense. This is a major task of the social sciences generally, and a central focus of many specific fields of research.4 Currently, studies seeking to understand social change often make inferences about longitudinal relationships based on the results of cross-sectional research. Ruiter and van Tubergen (2009), for example, derive conclusions

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3 On the other hand, Maas and Hox (2005) show that while small numbers of level-2 units introduce bias in the error terms, the bias is not large except for very small numbers.

4 As De Boef and Keele (2008: 184) put it, “research in all subfields of political science is devoted in large measure to understanding the causes and consequences of events, opinions, behavior, and institutional change as they unfold over time.”
about the long-term process of secularization from their cross-sectional study of religious attendance. And on the basis of their cross-sectional study of unionization, Martin and Brady (2007) argue that when a country signs an agreement with the IMF, there is a decline in the probability of a given resident of that country being a union member. Efforts to draw conclusions about social change based on cross-sectional research are not necessarily wrong, but they are clearly dependent on the assumption that longitudinal and cross-sectional relationships are the same.

The problem is that this assumption will in many instances not be valid. Researchers working with national-level time-series cross-sectional data (TSCS, discussed further below) have found that such data typically fail a standard Hausman (1978) test of whether cross-sectional and longitudinal effects are equivalent (e.g., Gray, Kittilson, and Sandholtz 2006; Milner and Kubota 2005). By implication, the longitudinal and cross-sectional relationships in the data are different, and merging them will be misleading. For this reason, analyses of TSCS data often employ “fixed effects” or “within” models, where the goal is to explain divergent patterns of change over time. Such models use dummy variables to hold constant and thus control for differences among countries—even at the cost of losing the ability to investigate the sources of any differences across countries. The prevalence of fixed effects models in analyses of TSCS data is precisely due to the non-equivalence of the “between” and “within” effects.

From the perspective of another, very different field of study, psychological research on individuals, Molenaar (2004) makes a similar point: patterns in the differences among individuals are not the same as patterns in the differences within individuals over time. Where research seeks to study change over time, it is preferable to do so directly, using longitudinal data and comparisons, rather than inferring longitudinal relationships from purely cross-sectional data and comparisons.

3 Characterizing Longitudinal Comparative Survey Data

Before the next section proceeds to a more detailed discussion of specific multilevel modeling techniques, this section briefly highlights some key features of longitudinal comparative survey data, and of multilevel models fitted to such data.

First, longitudinal comparative survey data are a sub-category of repeated cross-sectional survey data. The latter are not necessarily comparative, where comparative here means that respondents’ membership in larger macro-level units is one of their key characteristics, insofar as it allows for comparisons among those higher-level units. A study of repeated cross-sectional survey data, where all respondents are drawn from a single higher-level unit, would not be comparative, in this sense.

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5 Time-invariant country-level variables cannot be included because they would be perfectly collinear with the country dummies. “Within” models—which examine changes within countries over time—can be contrasted with “between” models that contrast countries cross-sectionally.

6 Less often, TSCS data are analyzed using multilevel (“random effects”) models, where country-observations are the level-1 units, and countries are the level-2 units; in this case, random intercepts substitute for the country dummy variables used in fixed effects models. Western (1998) is one prominent example of this type; he uses a Gibbs sampler in fitting a model of the political determinants of economic growth rates. Shor, Bafumi, Keele, and Park (2007) provide a fuller methodological discussion, and argue that compared to ordinary least squares with fixed effects or panel-corrected standard errors, the advantages of the multilevel approach include “vastly increased flexibility in model specification, potential improvements in model fit, and better accounting of uncertainty at all levels of analysis” (166).
Second, although societies are by no means reducible to their component members, and survey data are collected on individuals, such data are often sought specifically because they are, in aggregated form, an effective means of measuring differences among societies and for tracking changes in societies over time. But despite the frequency with which survey data are considered in aggregated form, statistical analyses of aggregated data are less informative than those of un-aggregated, individual-level data. An analysis based on aggregated data can even be highly misleading, insofar as it risks committing an ecological fallacy, where aggregate-level relationships are erroneously assumed to hold also for the individual units on which the pre-aggregated data were collected (see Diez-Roux 1998, and Subramanian et al. 2009—the latter revisit a classic analysis by Robinson 1950). To take one notable recent example, Gelman et al. (2008) show that voters in American states with higher average incomes have recently tended to vote more for Democratic than Republican candidates. While an analysis using data aggregated to the state level would therefore suggest that Democratic voters tend to be wealthy elites, that is not in fact the case, since within any given state Democratic voters have tended to be lower income-earners than Republican voters. A purely aggregate-level analysis in this case would therefore be deeply misleading. In contrast, multilevel models fitted to individual-level survey data are a means of not risking an ecological fallacy, while still allowing for the investigation of differences among the macro-level units in which respondents are nested.

Third, the data drawn from multiple waves of a comparative survey, where different individual respondents are sampled in each wave, are not generally referred to as panel data; each respondent is observed only once, and panel data are typically defined as data based on repeated observations on the same units. But insofar as societies are units of analysis at least as important as the individuals on which observations are made, then in an important sense the data derived from social surveys are in fact panel data, since societies are each observed multiple times.

Fourth, macro-comparative social scientists working with quantitative country-level data tend to draw a firm distinction between panel data and time series cross-sectional (TSCS) data—the latter being more their stock-in-trade (Beck 2001). TSCS data are a particular variant of panel data, where the number of units observed on repeated occasions is small (since the units are usually a non-random sample of countries), but the number of measurement occasions is large. A classic "long-form" TSCS dataset might have 600 rows—consisting of annual observations on 20 countries over a 30-year period. Examples of topics that can be investigated using country-level TSCS data include the changing status of women in society (Gray, Kittilson, and Sandholtz 2006), the growth of government spending over time (Kittel and Winner 2005; Plümper et al. 2005), or the rise of economic globalization in the late 20th century (Milner and Kubota 2005). In contrast to TSCS data, panel datasets often include hundreds or thousands of units, such as a random sample of individuals, where each unit is observed only a few times—maybe even just twice.

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7 Note the title of Hyman’s (1991) book on the history of survey research, Taking Society’s Measure.

8 In recent years, the increasing availability of quantitative data for larger numbers of countries—often now more than 100—has increased typical number of countries included in TSCS analyses. See for example Gray, Kittilson, and Sandholtz 2006; Milner and Kubota 2005.

9 Note that an individual-level panel dataset is a specific kind of repeated cross-sectional data—precisely the same individuals are observed multiple times—whereas in the typical case of longitudinal comparative survey data, different individuals are surveyed in each wave.
As noted by Beck (2001), different analytical methods are appropriate for panel (large \(N\), small \(T\)) and TSCS (small \(N\), large \(T\)) data.

Typical longitudinal comparative survey data can be considered simultaneously (a) non-repeated observations on a large random sample of micro-level units, and (b) repeated observations on a small non-random sample of macro-level units—the latter bearing some similarities to TSCS data.

4 Existing Models of Comparative Longitudinal Survey Data: De Facto Pooling

Many previous studies have relied on multilevel models in studying the drivers and/or mechanisms of social change through survey data analyses. In this section, I will review one approach that has been applied to longitudinal comparative survey data.

To fix ideas, a straightforward two-level model, where individual survey respondents (indexed \(i\)) are nested within higher-level societal units (indexed \(j\), typically countries), can be written as:

\[
y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij}, \quad i = 1 \ldots I, j = 1 \ldots J,
\]

where each \(j\) has random intercept (or group-level disturbance) \(u_j\), and both \(u_j\) and the individual error term \(e_{ij}\) are distributed Normally. The \(x\) variables can be either variable within countries (and are subscripted \(ij\)) or invariant (\(j\)). The random intercepts are assumed to be uncorrelated with both \(x\) and \(e\).

Among the few previous studies that have incorporated multiple waves of comparative survey data, the dominant approach has been to fit a three-level model, where respondents (\(i\)) are nested within country-years (\(t\)), nested in turn within countries (\(j\)). Such a model can include a coefficient capturing the effect on \(y\) of an \(x\) variable that varies both across countries and within countries over time. This \(x\) variable is considered to be a characteristic of country-years, and is indexed \(t_j\), because it is constant for individuals within a given country-year, and non-constant across both countries and the country-years nested within a given country:

\[
y_{ij} = \beta_0 + \beta_1 x_{1ij} + u_j + u_{ij} + e_{ij}. \quad (2)
\]

Figure 1 illustrates the three-level character of such models. Individuals \(i=1\) and 2 are observed at (and nested within) time \(t=1\), while individuals \(i=3\) and 4 are observed at time \(t=2\); individuals observed at both times are nested within country \(t=1\). The arrow of time flows through the second level of the model.
Jen et al. (2009) adopt this approach, for example, in their test of Wilkinson and Pickett’s (2006, 2009) hypothesis that societal-level income inequality tends to lead people to have poorer health (the latter supported by multilevel analyses of individuals nested in U.S. states—e.g., Kennedy et al. 1998). Solt (2008) does the same, in studying the effect of inequality on political engagement. This approach investigates social change only in the limited sense that, in making use of all the available survey data, those data happen to have a longitudinal dimension. Though the x variable of interest varies both over time and across countries, these two dimensions of its variability are treated singly—making it impossible to know whether just one dimension is driving any covariation found with y, or even potentially whether the two effects have opposing signs. This approach effectively assumes that the cross-sectional and longitudinal associations between x and y are the same: a single coefficient $\beta_1$ linked to variable $x_{jk}$ captures both effects. That assumption of equivalence, as discussed earlier, will often be unjustified.

5 Distinguishing Between Cross-Sectional and Longitudinal Effects

I now turn to extensions of existing multilevel modeling techniques that address the limitations of existing approaches. The first extension I describe allows for the simultaneous but separate analysis of cross-sectional and longitudinal effects. The technical requirement for distinguishing between cross-sectional and longitudinal effects is embarrassingly simple: calculating a mean, and subtracting that mean from the original x variable of interest. This approach has been applied by the author in Fairbrother and Martin (2011), in a test of Uslaner’s (2002) hypothesis that the level of inequality in a society is the main determinant of its members’ willingness to trust generalized others.

The technique entails the following. Recall that the goal is to estimate, separately but simultaneously, a cross-sectional and a longitudinal effect. That goal can be fulfilled by group mean-centering the covariate of interest.

To identify separate longitudinal and cross-sectional associations between an x variable and a y variable, calculate the mean of that x variable across all level-2 units (country-years) for each country, pooling all relevant years. This country mean variable captures the effect of enduring differences across countries in x on the y variable of interest. To capture the effect of variation in that x variable over time within each country, the overall country mean is then subtracted from each specific country-year x. The cross-sectional component ($\bar{x}$, a country-level variable) and the longitudinal component (x - $\bar{x}$, a country-year level variable) are thus orthogonal to each other by construction, and their effects can be estimated separately.

The resulting model is:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 \bar{x}_{2ij} + \beta_3 \text{time}_{ij} + u_i + u_{ij} + e_{ij}.$$  \hspace{1cm} (3)

Here the original variable x has been decomposed into a time-invariant country mean ($\bar{x}$) and a time-varying de-meaned component ($x_{1ij}$). The equation also includes a variable for time—this could be a set of year dummies and/or a linear effect.

This extension, which allows for both a “between” and “within” effect, represents an important improvement on existing techniques: it provides a direct investigation of social change without assuming that the longitudinal relationship is the same as the cross-sectional relationship. This extension investigates a specific relationship: the possible covariation between a shift in x over time and a shift in y over time. This relationship can be investigated even as the cross-sectional association between some time-invariant x and the level of y is also estimated.
There are precursors to this extension. Previous studies and commentaries have remarked on the benefits of group mean centering when fitting multilevel models (see for example Paccagnella 2006; Raudenbush 1989; Wu and Wooldridge 2005). In analyses of social change using longitudinal analyses of national-level TSCS data, Bartels (2008) has recently argued for the benefits of the technique. Moller, Alderson, and Nielsen (2009) use group mean centering in analyzing the drivers of cross-sectional and longitudinal variations in U.S. counties’ levels of inequality. But prior to Fairbrother and Martin (2011), this technique has not been applied to the analysis of individual-level survey data.

6 Societal Growth Curves

The technique introduced in the previous section investigates the association between a shift in \( x \) over time and a shift in \( y \) over time, but it does not investigate whether the absolute (high versus low) level of a slow-moving or even time-invariant variable \( x \) leads to faster versus slower change in (or growth of) \( y \). Yet, as Plümper et al. (2005) note, in studies of longitudinal relationships, one would ideally want to allow for these “level effects.” This section introduces a technique for doing precisely this. The technique is the application of “growth curve modeling” to the higher level units in longitudinal comparative survey data.

“Growth curves” are multilevel models where measurement occasions are nested within individuals who are observed multiple times (see e.g., Singer and Willett 2003). Such models have long been applied to individual-level panel data, such as in psychology or education research. Canonically, growth curve analyses have been used in studies of child or adolescent development (e.g., Willett, Singer, and Martin 1998), and have answered questions about how some feature \( y \), such as performance on a test of mental or physical ability, changes as subjects age. Such models allow for the possibility that change in \( y \) over time varies not with change in \( x \), but according to the absolute (and perhaps constant) level of \( x \)—for example gender, family size, or some characteristic of the home environment.

Mathematically, just as distinguishing between cross-sectional and longitudinal effects involved no more than a simple decomposition, so too do growth curves require only a simple interaction between an \( x \) variable and time. A growth curve can be represented, using equations at two levels, as

\[
y_{it} = \beta_{0i} + \beta_{1i} time_{it} + e_{it},
\]

where \( y_{it} \) represents \( i \)’s score at time \( t (t = 1 \ldots T) \), \( time_{it} \) represents an index of time for individual \( i \) (whether continuous or categorical), and \( \beta_{0i} \) and \( \beta_{1i} \) represent a random intercept and time slope, respectively for \( i \). This is the level-1 equation. The intercept and slope parameters are random effects, which can vary across units, as indicated by their \( i \) subscripts. Two level-2 equations describing these parameters are then

\[
\begin{align*}
\beta_{0i} &= γ_{00} + γ_{01}x_{i1} + γ_{02}x_{i2} + u_{0i} \\
\beta_{1i} &= γ_{10} + γ_{11}x_{i1} + u_{1i} \\
e_{it} &\sim N(0,\sigma_e^2).
\end{align*}
\]

In the level-2 equations, the intercept term \( \beta_{0i} \) combines an overall intercept \( γ_{00} \), time-invariant and time-varying covariates \( x_{i1} \) and \( x_{i2} \) (with coefficients \( γ_{01} \) and \( γ_{02} \) respectively), and a random intercept unique to each \( i \), denoted as \( u_{0i} \). Similarly, the time slope \( \beta_{1i} \) is the sum of an overall slope \( γ_{10} \), a time-constant covariate \( x_{i2} \) with coefficient \( γ_{11} \), and an \( i \)-specific random disturbance \( u_{1i} \). The covariance of the
random intercepts and slopes is estimated. The strength of the growth curve model is that it allows for the linear fixed effect for time \( \beta_{1j} \) to be a function of one or more time-invariant covariate(s) of interest, allowing for the rate of some change over time to be a function of these time-invariant predictors (Collins 2006). Growth “curves” are often curvilinear (with quadratic functions of time) but can also be linear or discrete.

For analyses of comparative longitudinal survey data, I propose the use of “societal growth curves.” A societal growth curve is, as the name implies, a growth curve at the societal level rather than the individual level. Since societies are observed multiple times in repeated cross-sectional survey data, the pattern of change of each one through time can be described using a curved or straight line. A societal growth curve illustrates the pattern of change over time—the rate of change and the height of the original starting point.

How can growth curve analysis be applied to whole societies, where observations on those societies are collected via observations on individuals? A societal growth curve model fitted to repeated cross-sectional individual-level survey data can be specified as:

\[
Y_{ij} = \beta_{0j} + \beta_{1j}t + \beta_{3j}t^2 + e_{ij}
\]

\[
\beta_{0j} = \gamma_{00} + \gamma_{01}x_{1j} + \gamma_{02}x_{2j} + u_{0j}
\]

\[
\beta_{1j} = \gamma_{11}x_{2j} + u_{1j}
\]

\[
\beta_{3j} = \gamma_{20} + \gamma_{21}x_{4j} + u_{3j}.
\]

(6)

Here \( \gamma_{00} \) refers to the overall intercept, \( \gamma_{01} \) denotes the fixed effect of country-level covariate \( x_{1j} \), \( \gamma_{02} \) denotes the fixed effect of individual-level covariate \( x_{2j} \), and \( u_{0j} \) is a country-\( j \)-specific random intercept. In the second of the stage-2 equations, \( \gamma_{11} \) refers to the fixed effect of a country-year-level variable \( x_{2j} \) and \( u_{1j} \) is a country-year-level random intercept. In the third of the stage-2 equations, \( \gamma_{20} \) denotes the fixed effect for time (the average time slope across all units), \( \gamma_{21} \) to the effect of some time-invariant country-level covariate \( x_{4j} \) on the time slope, and \( u_{3j} \) to the random disturbance for each country \( j \). Thus the outcome \( y \) for individual \( i \) in country \( j \) observed at time \( t \) is the sum of an intercept, fixed effects at the country, country-year, and individual levels, random intercepts for countries and country-years, an individual-level disturbance, and the effect of time—the slope of the latter being the sum of an overall trend, a country-level covariate, and a country-level random disturbance.

Finally, to make the model as general as possible, it should be flexible in allowing for change to occur via a variety of mechanisms. Survey respondents are embedded in time in three different ways. They have been alive since birth for a given length of time—their age. The country in which they live is moving through time, and they are interviewed at a specific moment—the period. And they were born at a specific moment in history—their cohort. Society can change either via period effects, wherein members of society experience gradual or rapid changes as time goes by, or via cohort effects, whereby social change may occur even if no single individual changes over the course of his or her life. In the latter case, society changes because older generations die out and are replaced by younger generations, who are different in their attitudes, behaviors, or whatever (Ryder 1965).

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10 I use the term “growth curve” because it is well-established for the analysis of individual-level data, not because social changes must be considered “growth,” with its connotations of maturation and/or development.

11 The spirit of this flexibility embodies that of De Boef and Keele (2008), who caution that the specifications of many longitudinal models possess important restrictions that may lead to biased and misleading inferences. The longitudinal effects of a given \( x \) variable can be rendered undetectable by an incorrect (overly restrictive) specification.
Much research on social change has found that cohorts, rather than periods, are the major mechanism by which change occurs—though there are important exceptions. To test theories of social change, and allow for all reasonable possible kinds of change, we need to allow for both of these mechanisms. Recent methodological work suggests that age, period, and cohort effects can be distinguished (Yang 2008; Yang and Land 2008), but this can only be done given strong assumptions based on substantive knowledge not derived from the data. Entirely different combinations of age, period, and cohort effects can generate precisely the same observable data (Glenn 1989). The multilevel methods proposed here make no assumptions about the mechanism by which change occurs—period or cohort effects.

**Illustrative Application(s)**

Here I might talk about religiosity, for instance...

**Conclusions**

From the point of view of political science, in introducing a special issue of Political Analysis devoted to multilevel models, Orit Kedar and W. Phillips Shivel (2005) write that “one could reasonably claim that all comparative politics is multilevel.” By this, they meant that individual-level relationships will almost inevitably vary from country to country, and therefore studies of such relationships will benefit from national-level contextualization.

In general, across the social sciences, a typical goal of much research is to explain social change. Such change is often, though not always, an aggregate effect. Repeated cross-sectional survey data would appear to be a natural tool for this work, and to some extent such data are already being put to work. However, existing applications do not fully exploit the properties of such datasets, and because of their specifications they risk overlooking, and deriving misleading inferences about, important relationships.

This paper has not addressed the issue of the time series properties of the longitudinal data, but careful consideration must be given to autocorrelation and the possibility that a series is non-stationary. In principle, time series in x can be tested for non-stationarity using typical techniques, while the possible non-stationarity of y could be checked using the same techniques applied to the \(ij\) random intercepts from a null model.

**References**


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12 In practice, however, most articles included in the special issue use two-step regression rather than a genuinely multilevel approach.


