Multilevel Thinking

Discovering Diversity, Universals, and Particulars in Cross-Cultural Research

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1 The Usefulness of Multilevel Modeling and Multilevel Thinking

"I am because we are; and since we are, therefore I am." (Mbiti, 1970)

For decades now, multilevel models have been an important quantitative tool for social research. While multilevel models have become very common in social research, there are aspects of these models that are explored less frequently in published articles that appear in academic journals. This book arises from my experiences of teaching a course entitled *Multilevel and Longitudinal Modeling* that I have taught for over a decade in the *Joint Doctoral Program in Social Work and Social Science* at the University of Michigan.

The book started out as a set of notes on *things I only get to discuss during breaks, or after class, or during office hours* in my class on *Multilevel and Longitudinal Modeling*, and has grown from that set of notes into an introduction to multilevel modeling.

My contention is that *multilevel modeling* offers powerful tools for understanding the *multilevel data* that social researchers often confront. For example, researchers are often interested in studying outcomes for diverse groups of children in different schools, residents of diverse and different neighborhoods, or individuals or families living in diverse and different countries. Such inherently multilevel data lead to analytic complexities, some of which appear to me to be well understood, while others seem to be much less often appreciated.

The point that I wish to make about multilevel data is that when presented with complex multilevel data, failure to use the appropriate multilevel model may lead to conclusions that are demonstrably incorrect. Fortunately, many of these difficulties can be avoided with applications of simple and straightforward multilevel models.

I start by presenting some initial ideas about multilevel modeling. First, as is relatively commonly understood, *multilevel models allow for the correct estimation of p values in the presence of data clustering*. Second, as is less commonly appreciated, when data are clustered, *multilevel models correctly estimate β regression coefficients and may avoid estimating a regression coefficient that is too large, too small, or even has the wrong sign.*

I go on to explore some more complex ideas about multilevel models that I see less often in the published empirical literature. I focus especially on two ideas: *multilevel models as the exploration of diversity and variation across countries and cultures*; and *multilevel models as a foundation for models that let us think more rigorously about causality.* I argue that multilevel models provide a foundation for engaging with cross-cultural diversity in a quantitatively rigorous fashion.

Certainly, none of the statistical ideas contained in this book are unique to me. There are thorough–and often much more mathematically rigorous–presentations of many of the ideas contained in this book in some of the excellent foundational texts on multilevel modeling such as the early book by Raudenbush & Bryk (2002), the excellent book on longitudinal models by Singer & Willett (2003), excellent books by Snijders & Bosker (2012) and Hox et al. (2018), and Rabe-Hesketh & Skrondal (2022)'s more recent and extremely comprehensive two volume text. Luke (2004), and Kreft & de Leeuw (1998), offer shorter, less mathematically rigorous, but still excellent introductions to the topic of multilevel modeling. Gelman et al. (2007) introduced me to the ideas that in this book I describe as "multilevel structure" using an example with voting patterns.

My intent in this book is to offer a kind of accessible tutorial for applied researchers, including especially those who see their research having some advocacy based component. My approach, while offering up some equations, is less mathematically rigorous than some of the above mentioned texts, and written with the intent of providing a clear and practically focused guide for the applied researcher who is attempting to carry out better research with diverse populations, particularly research directed toward advocacy or social change.

Acknowledgements

No good learning happens without community. At least, that has always been true for me. I am grateful for many creative and energizing discussions with the other members of the MICS (UNICEF data) research team: Professor Julie Ma, Dr. Kaitlin Ward, Professor Garrett Pace and Professor Shawna Lee. I'm thankful for their collegiality, their friendship, their patience with me, and their dedication to good science. Working with these colleagues has greatly deepened my understanding of multilevel models. I'm also very grateful to one of my mentors, Professor Sandra Danziger, who has taught me so much about the *what* and the *why* of mentoring, teaching, and doing research. My colleagues Professor Karen Staller, and Professor Julie Ribaudo have also helped me clarify my thinking about the *what* and the *why* of research and teaching, and have encouraged me along the way. Don Deutsch showed ongoing interest in the development of this book, and has asked some hard questions that have improved its logic. Thank you to Professor Jim Allen for our discussions about how quantitative methods can better listen to lived experience. Importantly, I'd like to express gratitude to the many students in my class on *Multilevel and Longitudinal Modeling* who over the years have helped me think more deeply about statistical and substantive issues, including Dr. Kaitlin Ward, Professor Garrett Pace, Professor Julie Ma, Professor Yoonsun Han, Professor Berenice Castillo, Professor Maria Galano, Dr. Sara Stein, Madhur Singh, and Tong Suo. Thank you for the many valuable discussions during class breaks, and after class. These discussions have also greatly extended my understanding of multilevel models. I'd like to thank Marty Betts and Greg Knollmeyer for their help and support. Most importantly, I have two last people to thank: I'd like to thank Ross Grogan-Kaylor for continued interest in the progress of this book, and probing thoughtful questions. Shari Grogan-Kaylor had many important and challenging questions about the *what* and the *why* of this book, and most importantly to me, *has believed* in it. While I'm thankful for the inspiration and support provided by others, any remaining errors and omissions in this book are of course my responsibility.

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Some Preliminary Thoughts

> "Like you I
>
> Love love, life, the sweet smell of things, the sky-blue landscape of January days.
>
> ...
>
> I believe the world is beautiful.
>
> And that poetry like bread, is for everyone.
>
> And that my veins don't end in me.
>
> But in the unanimous blood.
>
> Of those who struggle for life,
>
> Love, little things,
>
> Landscape and bread, the poetry of everyone."

— (Dalton, 2000) (translated By Jack Hirschman)

> “A lifetime is too narrow to understand it all, beginning with the huge rockshelves that underlie all that life.
>
> No one ever told us we had to study our lives, make of our lives a study, as if learning natural history or music, that we should begin with the simple exercises first and slowly go on trying the hard ones, practicing till strength and accuracy became one with the daring …
>
> But there come times—perhaps this is one of them—when we have to take ourselves more seriously or die, when we have to pull back from the incantations, rhythms we’ve moved to thoughtlessly, and disenthrall ourselves, bestow ourselves to silence, or a severer listening …”

— (Rich, 1984)

> “Research is formalized curiosity. It is poking and prying with a purpose.”

— (Hurston, 1942)

2 Introduction

> "Sure, it's hard to get started; remember learning to use knife and fork? Dig in: you'll never reach bottom. It's not like it's the end of the world–just the world as you think you know it." (Dove, 1999)

> "Listening to the world. Well, I did that, and I still do it. I still do it." (Mary Oliver in Oliver & Tippett, 2015)

2.1 Quantitative Methods and Social Justice

There is clearly need for both qualitative and quantitative methods. Central to the argument of this book is the idea that advanced quantitative methods can be core contributors to the agenda of understanding issues of diversity and social justice more fully and thoroughly (Cokley & Awad, 2013; Grogan-Kaylor et al., 2018). Quantitative methods, particularly in discussions comparing qualitative and quantitative methodologies, are sometimes labelled as inherently *positivist* methods. My argument regarding this point is twofold. First, there is nothing within the mathematics of quantitative methods that requires a positivist epistemology. Quantitative methodologies could as easily be conducted using a critical epistemology–that is aware of dynamics of power and privilege–as any other methodology (Scharrer & Ramasubramanian, 2021; Stage & Wells, 2014). I note that one of the pioneers of liberation psychology, Martin-Baró (Aron & Corne, 1994), used both qualitative and quantitative methods (Martin-Baro, 1994a), including in the latter case, relatively sophisticated arguments about patterns of missing data across a survey data set (Aron & Corne, 1994).

Second, when we have samples of a hundred, several hundred, several thousand, or even hundreds of thousands of study participants distributed across multiple and diverse social contexts, it is difficult to imagine a methodology other than a *quantitative* methodology that could accomplish the following:

1. Sift through thousands of responses, and determine the *overall, or average, pattern of relationships* between risk factors, protective factors, and outcomes.
2. Determine whether there is evidence that the relationships observed within the data are more than *statistical noise*.
3. Adjudicate the *complex multivariate relationships* of risk factors, protective factors and outcomes, while controlling for possible confounding variables, contextual variables, or background variables.

Additionally, it is difficult to imagine a methodology other than a *quantitative multilevel* methodology that could accomplish the above 3 goals, and could additionally:

4. Explore the *diversity and variation and commonalities in these relationships* across social contexts.

Therefore, I consider multilevel modeling to be a principled quantitative method for *listening* to the voices of large numbers of study participants across social contexts. In Section 6.7.5, I consider the way issues of omitted variables–an often under-appreciated issue–contribute to the difficulty of obtaining *correct* answers in all quantitative work. In Section 5.2.1, where I consider the estimation of p values, and Section 5.2.2, where I consider the signs of regression coefficients, I explore the ways that *multilevel data* can contribute substantially to the complexity of the analysis of data. This complexity of *multilevel data* means that unless one employs appropriately sophisticated *multilevel analysis* methods with *multilevel data*, one runs a relatively high risk of making *incorrect substantive conclusions.* I thus argue that advanced quantitative methods, like multilevel modeling, can play an important role in contributing to liberatory ideas and to social justice.

There is an ethical argument that is embedded in this book. Many of us do research with the hope of better understanding the relationship of risk and protective factors with outcomes in diverse, and often disadvantaged or marginalized, populations. Many of us further hope that our work might be part of conversations about appropriate polices, programs, treatments or interventions. Given the frequent vulnerability and marginalization of the people with whom we work, when using quantitative methods, it is incumbent upon us to employ methods that adequately address the complexities of the data, that offer an appreciation of the variability and diversity within the data, that provide the most accurate and unbiased estimates possible, and that increase the probability of obtaining *correct* answers to important substantive questions.

> "It is hard to imagine that anyone with a humanitarian worldview would argue against the need for a more quantitatively literate citizenry. Informed political decision-making, retirement planning, active parenting, and the vast majority of choices we make in our personal, occupational, and civic lives can be better served by improved quantitative understanding and reasoning, as well as accompanying action-oriented dispositions." (Wiest et al., 2007)

The idea of this book is that a deeper study of multilevel modeling can result in an advanced "quantitative literacy" (Wiest et al., 2007), "quantitative criticalism" (Scharrer & Ramasubramanian, 2021), "critical quantitative inquiry" (Stage & Wells, 2014), or "principled argument" (Abelson, 1995), that is appropriate for drawing accurate conclusions from multilevel data.

2.2 Some Philosophy of Science

I am not much of a philosopher of science. However, I am very persuaded by Strevens' (2020) minimalist criterion of the "iron rule". In essence, this rule specifies that to count as "science", investigations must engage in "performing an experiment or making an observation that generates relevant empirical evidence" against which competing hypotheses can be tested. A similar perspective is offered by Goldacre (2011) who argues that ideas about interventions should be scrutinized with a "fair test". That is to say, they should be tested against evidence that can support or refute those ideas. I would argue all ideas about promoting human well-being should be able to be subjected to such a "fair test".

I believe that our work—whether qualitative, or quantitative—should strive to be both critical *and* scientific, in the sense that: our research should gather evidence; that evidence should be assessed in order to support, refute, or modify our initial beliefs; and that evidence should be used to think critically about human wellbeing, including dynamics of power and privilege and disparities. With regard to this idea, Shrader-Frechette (2014) suggests that a "practical philosophy of science" can contribute both to "speaking truth to power" and to "seeking justice".

2.3 A Pragmatic Approach

This book will discuss the ways in which a multilevel statistical perspective not only allows one to appropriately analyze cross cultural or international data, but also the ways in which a multilevel perspective affords the opportunity for more precise quantitative thinking about cross cultural phenomena. The book takes a very pragmatic and very advocacy oriented approach to improving research.

> "It shouldn't be theories that define the problems of our situation, but rather the problems that demand, and so to speak, select, their own theorisation." (Martin-Baro (1998) in Burton & Kagan (2005)).

> "What we see and how we see is of course determined by our perspective, by the place from which we begin our examination of history; but it is determined also by reality itself." (Martin-Baro, 1994b)

Following from this pragmatic and advocacy oriented emphasis, the book is largely oriented to the *doing* of quantitative social research with multilevel (or multi-country) data, and is therefore mostly statistical in nature.

The book moves quickly into detailed statistical arguments. Some of these statistical discussions may seem very technical, or even overly technical. However, an overarching theme of the book is that multilevel data contains hidden complexities. A lack of awareness of the complexities of multilevel data—e.g. complexities of multi-country data—might lead to statistical analyses that point in the wrong direction: yielding false positives; false negatives; or substantively wrong conclusions.

2.4 Are Answers from Social Science "Obvious"?

Closely related, I think to the the idea that quantitative research can advance issues of social justice, is the question of whether answers from social science are "obvious". If social science answers are obvious, then social science has limited abilities to make new discoveries, and to build scientific foundations for evidence. In contrast, if answers from social science are sometimes not obvious, then social science has a greater ability to make new discoveries and build new foundations for evidence.

I have been thinking a lot about the idea that *Everything Is Obvious, Once You Know The Answer*, as detailed in the book with this title by Duncan Watts (2011).

This seems to me especially true in social research. Arguably, some conclusions of social research may indeed be obvious. For example, it may be obvious that *Adverse Childhood Experiences* (ACEs) are associated with long term decreases in mental health. However, even obvious conclusions may need to be quantitatively documented, in order to legitimate programs and interventions, and to secure funding. I also observe that I think that there is often a *historical* dimension to what is considered "obvious": conclusions that are at first considered to be unlikely to be true, or even counter-intuitive, require the weight of accumulating evidence over time for these connections to become "obvious". It is likely that the "obviousness" of the relationship between ACEs and later physical and mental health problems did not become apparent until research began to document these relationships (e.g. Felitti et al. (1998)).

As another example, Proctor (2012) documents the way which smoking was first considered to be an *unlikely* cause of lung cancer; only over the course of several decades of research and discussion to become an *obvious* cause of lung cancer. A similar *historical* dynamic seems to be playing out in some research on parenting and child development. Despite decades of evidence indicating that corporal punishment has undesirable consequences for children (Gershoff & Grogan-Kaylor, 2016b), corporal punishment remains a disciplinary strategy endorsed by the majority of the American population (Hines et al., 2022).

In contrast sometimes the conclusions of social research may not always be obvious. For example:

1. There has been an ongoing debate about whether corporal punishment is more or less harmful when used by parents in social contexts, or communities where it is more common, or normative, or in contexts that are disadvantaged. Eamon (2001) suggested that "when environmental risk is high, parenting practices that are firmer and higher in control result in lower levels of young adolescent antisocial behavior." This echoes similar research by (Deater-Deckard et al., 1996) suggesting that physical punishment was harmful for European-American children, but not for African-American children. Later, larger sample research has found that this appears not to be the case: physical punishment is harmful for children in *all* groups (Gershoff & Grogan-Kaylor, 2016b, 2016a; Pace et al., 2019).
2. Using MICS Data (UNICEF, 2021), we conducted a study of the link between gender inequality and physical child abuse (Ma et al., 2022). We expected to find that higher levels of gender inequality led to higher levels of physical abuse for female children, but not for male children. Instead, we found that higher levels of gender inequality were associated with higher levels of physical abuse for *both* male and female children. Additionally, there was some slight evidence that male children were at higher risk of being abused than female children. Equally interesting was that we found that gender inequality was predictive of levels of child abuse, while country level GDP was not.
3. In a study of parenting during Covid-19 (Lee et al., 2022), we expected to find that households with children would experience *higher* levels of anxiety and depression than households without children. Instead, we found the opposite. Being in a household with children was generally *protective* against anxiety and depression.

In Section 4.3, Section 5.2.1 and Section 5.2.2, I provide specific examples of how multilevel data provides even more opportunity to present answers that are *not* obvious.

2.5 Presenting Advanced Statistical Ideas

In presenting advanced, statistical concepts, one is faced with a quandary. One can present statistical concepts in the most general terms, in terms of x and y. While perhaps the mathematically most general way to present ideas, a highly general (and abstract) presentation risks not being a good way of teaching the ideas, as it is sometimes difficult to apply abstract ideas to one's own specific area of research.

Alternatively, one can present statistical ideas in terms of specific substantive concepts. The risk of making use of a specific substantive concept is that while concrete examples are always helpful, it may be difficult for the reader to generalize from a specific example to their own area of research.

I ground this presentation in research that we have conducted on parenting and child development in international context (Grogan-Kaylor et al., 2021; Ma et al., 2022; Pace et al., 2019; Ward, Grogan-Kaylor, Pace, et al., 2021; Ward et al., 2022; Ward et al., 2023). For the presentation in this book, I use simulated data on these issues.

Using the simulated data, I refer to *predictors* and *outcomes*, and explore the ways that the multilevel model can contribute to understanding how relationships between predictors and outcomes might be similar, or might be different, across *social contexts*. In the examples presented below, I focus on two predictors, parental *warmth*, and parental use of *physical punishment* and focus on the *outcome* of *improved* mental health. I use the social context of different *countries* in our example.

It is my belief that while I use this specific set of examples, that the idea of studying *families in different countries* is generalizable enough to a multiplicity of diverse contexts, such that the reader can apply these ideas to their own area of interest, whether that be *children in schools*; *residents in neighborhoods*; or *people in different countries.*

2.6 Research on Parenting and Child Development in International Context

Research on parenting and child development has identified robust associations between parenting behaviors and child developmental outcomes. Broadly speaking, physical punishment is associated with increases in child aggression, child anxiety and child mental health problems (Gershoff & Grogan-Kaylor, 2016b), while warm and supportive parenting is associated with decreases in these outcomes (Khaleque & Rohner, 2002; Rothenberg et al., 2022). However, much of this research is conducted on North American samples (Draper et al., 2022; Henrich et al., 2010).

Barth & Olsen (2020) have argued, that children constitute a class of oppressed persons. If children are oppressed, then it is imperative to empirically determine what factors are promotive of children's well-being, and what factors constitute risk factors that contribute to decreases in children's well-being. Equally imperative–given the North American focus of so much research on parenting and child development (Draper et al., 2022; Henrich et al., 2010)– would be efforts to extend the study of parenting and child development to a broader, more global context. As part of such a research agenda, it is necessary to have quantitative tools that are able to determine the consistency of relationships in parenting and child development. That is, are the relationships between certain forms of parenting and child developmental outcomes, largely consistent across countries, largely different across countries, or somewhere in between?

2.7 Universalism And Particularity

> "My conception of the universal is that of a universal enriched by all that is particular, a universal enriched by every particular: the deepening and coexistence of all particulars." (Cesaire, 1956)

The specific domain of cross-cultural research on parenting and child development raises more general questions in cross-cultural research of *universalism* and *particularity*. With regard to child development it is universal that all children need some amount of emotional and material care to grow into healthy youth and healthy adults (Kottak, 2021). Further it is broadly understood that children should be protected from violence (UNICEF, 2014). This broad consensus is manifested in such documents as the Convention on the Rights of the Child (United Nations General Assembly, 1989) and the United Nations Sustainable Development

Goals (United Nations, 2022), representing global efforts to ensure the children are cared for, and are protected against violence.

At the same time, broad international efforts to improve children's well-being must engage with important considerations of cultural uniqueness. Put simply, parenting practices may vary widely between cultural groups (Gottlieb, 2002). Further, what is considered to be beneficial for children in one country or culture may not be considered to be beneficial in all countries or cultures. Similarly, what is considered to be detrimental in one country or culture may not equally be considered to be detrimental in all. Within the area of parenting and child development, most of the debate has focused around the question of whether physical punishment is equally detrimental in all settings, particularly whether physical punishment is detrimental in countries where it is especially common, or normative (Gershoff et al., 2010). Much less attention has been focused on the study of positive parenting internationally, and the degree to which the outcomes of positive parenting are consistent across countries remains understudied (Ward, Grogan-Kaylor, Ma, et al., 2021).

However, as global initiatives to improve child well-being and family life move forward, it becomes increasingly important to continue to collect internationally relevant data about parenting and child outcomes. If recommendations are to be made for policies, interventions, or treatments, such recommendations must be based on accurate balancing of that which is universal against that which is unique to particular cultural contexts. Thus it is necessary to employ statistical methods that are able to adequately and accurately analyze data across countries.

As I will outline below–and is evident in the literature (Hox et al., 2018; Kreft & de Leeuw, 1998; Luke, 2004; Rabe-Hesketh & Skrondal, 2022; Raudenbush & Bryk, 2002; Singer & Willett, 2003; Snijders & Bosker, 2012)–multilevel models are eminently suited for cross-cultural research in that they are not only able to *control for* the clustering of study participants within countries, but are also able to *explore the variation*–or *consistency*–of patterns of social life across countries.

3 Simulated Multi-Country (Multilevel) Data

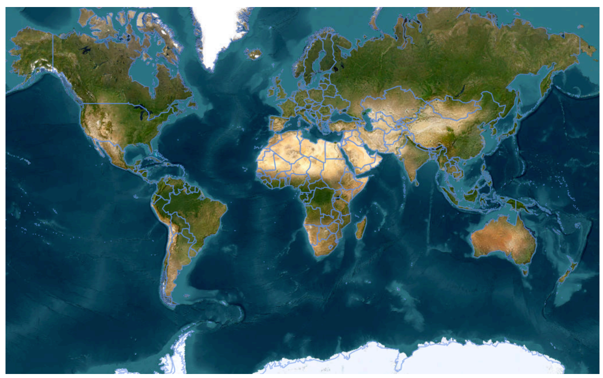

Figure 3.1: Countries of the World

> "… the particular and the universal are not to be seen as opposites, … the universal is not the negation of the particular but is reached by a deeper exploration of the particular." (Cesaire in UNESCO (1997))

I use simulated data in this example. Data come from 30 hypothetical countries. `country` is a numeric variable ranging from 1 to 30.[1] Data contain measures of a few key aspects of

[1] The `country` variable demonstrates an important point. Data for a grouping, nesting, or clustering variable does *not* need to identify the actual groups by name, but only needs to distinguish the groups from one another. Put another way, the data for the grouping variable can be anonymous about the actual identities of the grouping variable.

parenting[2] or caregiving that have proven salient in the empirical literature on parenting to date: parental `warmth`, and `physical punishment`. Both parenting measures are normally distributed variables, and are considered to be *Level 1*, or *individual level* variables.

`identity` is a hypothetical designation of an identity, such as a race, ethnicity, or gender identity. In this simulated data, identity has two categories–for ease of presentation–but could easily be a more than two category variable. `identity` is also a *Level 1* variable.

Many readers will be interested in using multilevel models to evaluate interventions. The variable `intervention` represents a program, treatment or intervention to which study participants have been assigned. `intervention` is a *Level 1* variable. Assignment to interventions may or may not be random, a topic which is considered in more detail in Section 6.7.

`HDI` is a measure of the *Human Development Index* (United Nations Development Program, 2022), and is measured at the *country level*, or *Level 2*. (I discuss more in depth thinking about levels of the data in Chapter 4.)

Our `outcome` is conceptualized as a positive mental health outcome or behavioral outcome, and higher levels of `outcome` are considered to be better. Statistically, the data are clustered within countries.

[2] I use the term parenting throughout this book, but am aware that such parenting may come from biological parents, or from other caregivers.

Download The Data

Data are presented in Stata format. The Appendix considers the analysis of multilevel models using multiple software packages: Stata, R & Julia, but Stata format is used to store the data as it can be read by each of these software packages.

- Cross-Sectional Data
- Longitudinal Data

In this simulation, I construct the data so that `warmth` is positively related to the `outcome`, while `physical punishment` is negatively related to the `outcome`.

Table 3.1: Simulated Multilevel Data

Table 3.1: Table continues below

id	country	warmth	physical_punishment	identity	intervention	HDI
1.1	1	3	3	1	0	69
1.2	1	1	2	1	1	69
1.3	1	2	3	0	1	69
1.4	1	5	0	1	0	69
1.5	1	4	4	1	0	69
1.6	1	3	5	0	1	69

Table 3.2: Simulated Multilevel Data

outcome
57.47
50.1
52.92
60.17
55.05
49.81

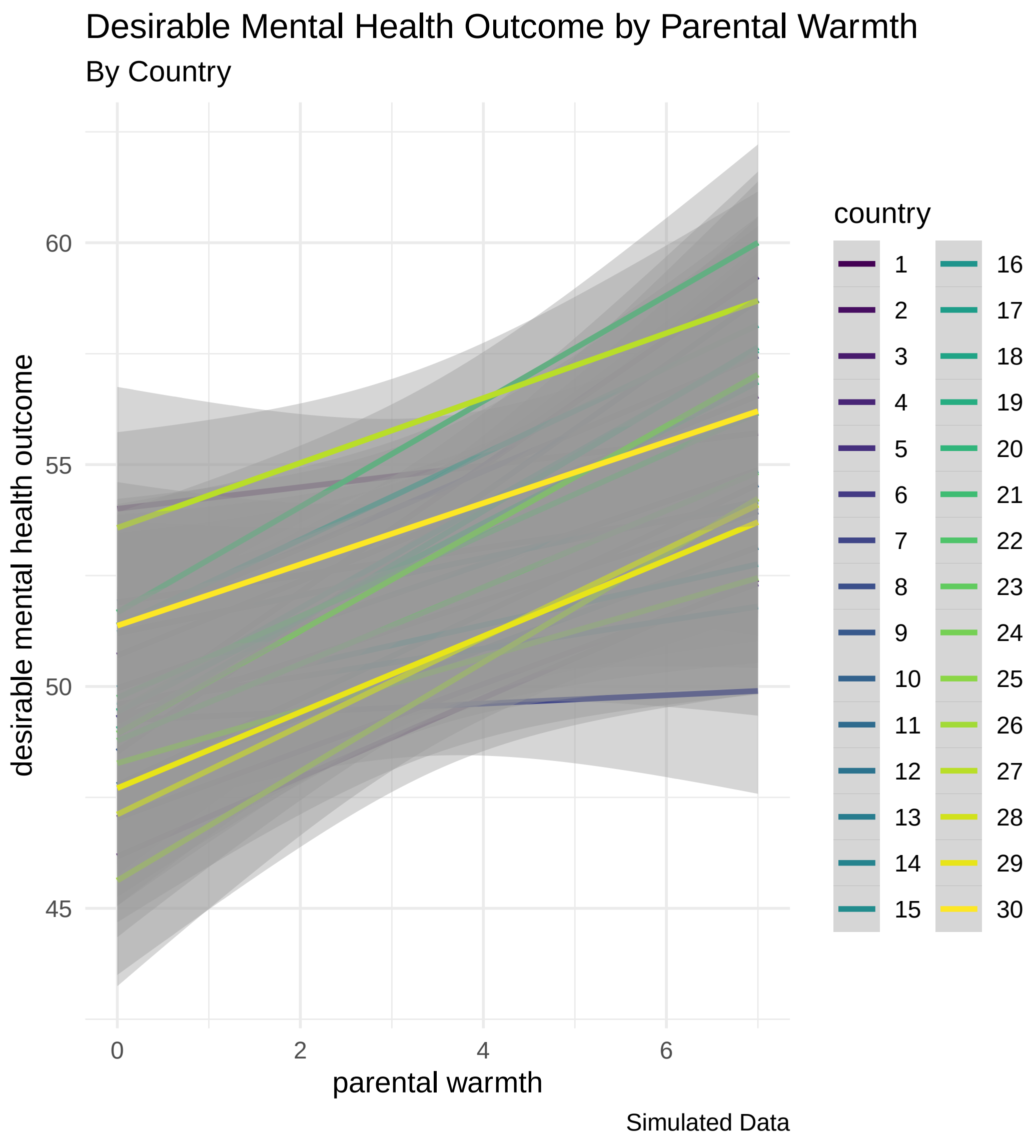

Figure 3.2: Graph of Simulated Data

4 Conceptual Framework

> "Ubuntu" defined as: "A person is a person through other people." e.g. in (Mangharam, 2017)

> "The language we have in that world is not large enough for the territory that we've already entered." (Whyte & Tippett, 2016)

4.1 Units of Analysis and Processes at Multiple Levels

When confronted with multilevel data, one has a number of choices about the units of analysis: one could consider individuals to be the units of analysis; or, one could consider the larger social units to be the units of analyses. With multilevel analytic methods, one is able to avoid this false dichotomy, and to conceptualize the data from a multilevel perspective, wherein both individuals and social units are different levels of the same analysis Raudenbush & Bryk (2002). I discuss some of the statistical implications of different ideas about the units of analysis in Section 5.9.

Further, with multilevel models, we are not only able to consider the idea of units of analysis at multiple levels of the data, but to consider how variables at both Level 2 and Level 1 may affect an individual level (Level 1) outcome.

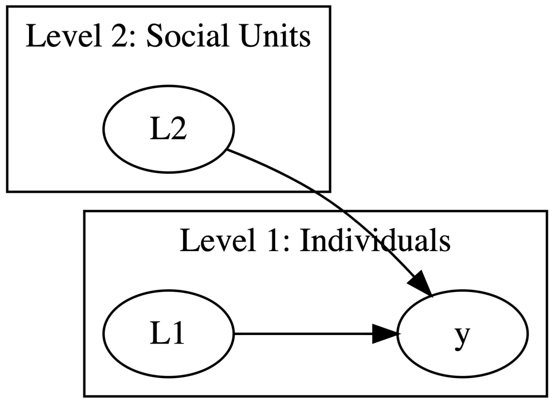

Figure 4.1: Conceptual Framework

4.2 Variables at Multiple Levels

In this book, I distinguish between *conceptual* and *statistical* levels of variables.

By *conceptual* level, I refer to whether a variable is *conceptualized* to be measure of an *individual* level characteristic, such as parenting or mental health, or a *community* level construct, such as community collective efficacy, or community safety.

By *statistical* level, I refer to whether a variable measures an *individual* response, or an *aggregated* response.

Table 4.1: Multiple Levels of Variables

	statistical level 1	statistical level 2
conceptual level 1	Individual response about parenting or mental health	Aggregated responses about parenting or mental health
conceptual level 2	Individual response about community	Aggregated response about community
conceptual level 2	N/A	Administrative indicator of social unit

- Thus, $\text{mental health}_{ij}$ or parenting_{ij} would be considered in the terminology that I am using to be a variable both *conceptually* and *statistically* at Level 1.
- $\overline{\text{mental health}}_{.j}$ or $\overline{\text{parenting}}_{.j}$ would be variables that *conceptually* come from Level 1 responses, but are *statistically* aggregated to Level 2.

Contextual Variables

Such aggregated variables represent the *average* level of a response across each Level 2 unit, and are sometimes called "contextual variables" (Diez Roux, 2002; Hox et al., 2018; Snijders & Bosker, 2012). These aggregated variables could be included in the model alongside the individual level, or Level 1, predictors. Consider:

$$y_{ij} = \beta_0 + \beta_1 \text{parenting}_{ij} + \beta_2 \overline{\text{parenting}}_{.j} + u_{0j} + e_{ij} \tag{4.1}$$

Equation 4.1 is be a model that includes parenting as a predictor of the outcome at two different levels. parenting_{ij} is a parenting behavior–whether discipline or warmth–at an *individual* level, while $\overline{\text{parenting}}_{.j}$ is a *contextual variable* representing the average level of parenting–whether discipline or warmth–at the *country* level. Equation 4.1 is thus testing whether parenting at the country level–a so-called country-level effect–has an association with the outcome over and above individual level parenting behavior.

Discussion of ways to create variables that are the average of a predictor is contained in the Appendix.

- Using my terminology, $\text{community collective efficacy}_{ij}$ or $\text{community safety}_{ij}$ would be considered to be a variable that was *conceptually* at Level 2, but *statistically* at Level 1.
- $\overline{\text{community collective efficacy}}_{.j}$ or $\overline{\text{community safety}}_{.j}$ would be variables that *conceptually* refer to Level 2 concepts that are *statistically* aggregated to Level 2.

Some variables only exist at Level 2, and their Level 1 counterparts are undefined. For example, the size of a school, neighborhood, or country, is inherently a Level 2 variable, with no easily definable Level 1 counterpart. Similarly, some administrative indicators, such as the Gini level of inequality, while developed by calculating across Level 1 responses, have no easily definable Level 1 counterpart.

4.3 Multilevel Models As The Exploration Of Variation and Diversity

Multilevel models are sometimes seen as an analytic technique that *controls for* the clustering or nesting of individuals inside larger social units such as schools, neighborhoods, or countries. I will describe below how this ability to *control for* clustering is indeed an important and crucial aspect of multilevel models.

However, my argument here is that multilevel models are better seen as a method to *explore* the variation and diversity inherent within nested or clustered data. Again, while these issues are well understood within the statistical literature (Hox et al., 2018; Kreft & de Leeuw, 1998; Luke, 2004; Rabe-Hesketh & Skrondal, 2012; Raudenbush & Bryk, 2002; Singer & Willett, 2003; Snijders & Bosker, 2012), they are less often noted in applied research.

4.3.1 A First Example: A Study Of Parenting And Child Development

In the graph below, imagine that physical punishment, or some other risk factor, is associated with detrimental mental health outcomes. Each country in the data has its own *country specific regression line*.

In Panel A, there is some variation in the *intercept*, which is equivalent to saying that there is some variation in the average level of psychological well-being across countries. When we look at the slope of the country-specific regression lines in Panel A, we notice that there is little variation in these *slopes*. Put another way, there is a great amount of consistency in the slopes

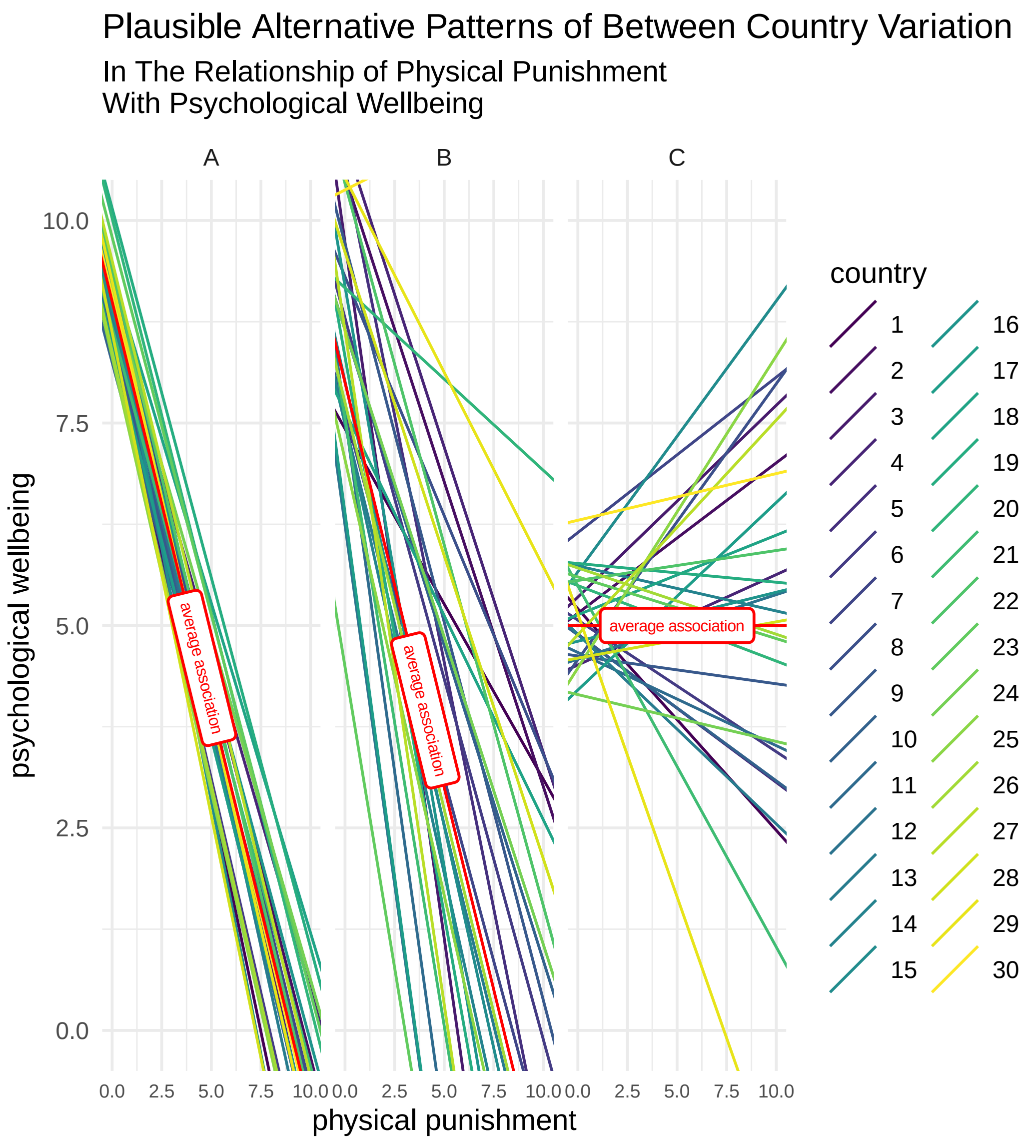

Figure 4.2: Plausible Alternative Patterns of Between Country Variation

of the country-specific regression lines: parental use of physical punishment is consistently associated with decreases in child psychological wellbeing across countries.

In Panel B, the situation is different. There is more variation in the *intercept*, that is, more variation between countries in the initial or average amount of psychological well-being. There is also more variation in the *slopes* of the country-specific regression lines. While the average association between physical punishment and psychological well-being is very similar to that in Panel A, there is more variation across countries, in the relationship of physical punishment and child psychological wellbeing, which would likely merit exploration were one considering developing programs, policies or interventions for different countries.

Lastly, the pattern of variation in Panel C is considerably different from either Panel A or Panel B. The average association of physical punishment with psychological well-being in the hypothetical scenario represented by Panel C is approximately 0. There is some variation in the *intercepts* of the country-specific regression lines. Additionally, there is considerable variation in the *slopes* of the country-specific regression line, suggesting that the use of physical punishment might be beneficial in some countries, and detrimental in others.

Empirically, data generally suggest a scenario somewhere between Panel A and Panel B, but these different hypothetical scenarios afford us the opportunity to think about possible patterns of variation.

4.3.2 A Second Example: A Study Of A Treatment Or Intervention

A second pedagogically helpful example might be obtained if we flip the slopes in the diagram, and consider a different set of independent variables, perhaps some kind of treatment or intervention designed to improve psychological well-being.

We see a similar pattern as before, but the use of a different substantive example may be illustrative.

In Panel A, there is relative consistency in the initial levels of psychological well-being across countries, as well as consistency in the degree to which the intervention is associated with improvements in psychological well-being across countries.

In Panel B, we see more variation in both initial levels of psychological well-being, but also more variation in the association of the intervention with improvements in psychological well-being.

Lastly, in Panel C, we note an overall association of the intervention with psychological well-being that is close to zero. However associations vary widely by countries. In some countries there appears to be evidence that the intervention is beneficial, while in other countries there appears to be evidence that the intervention is not beneficial, or even possibly harmful.

4.3.3 Exploring Variation

Thus, I emphasize an approach to multilevel modeling that sees multilevel modeling as the *study of variation* or an *exploration of variation*, not simply *accounting for variation*, or *con-*

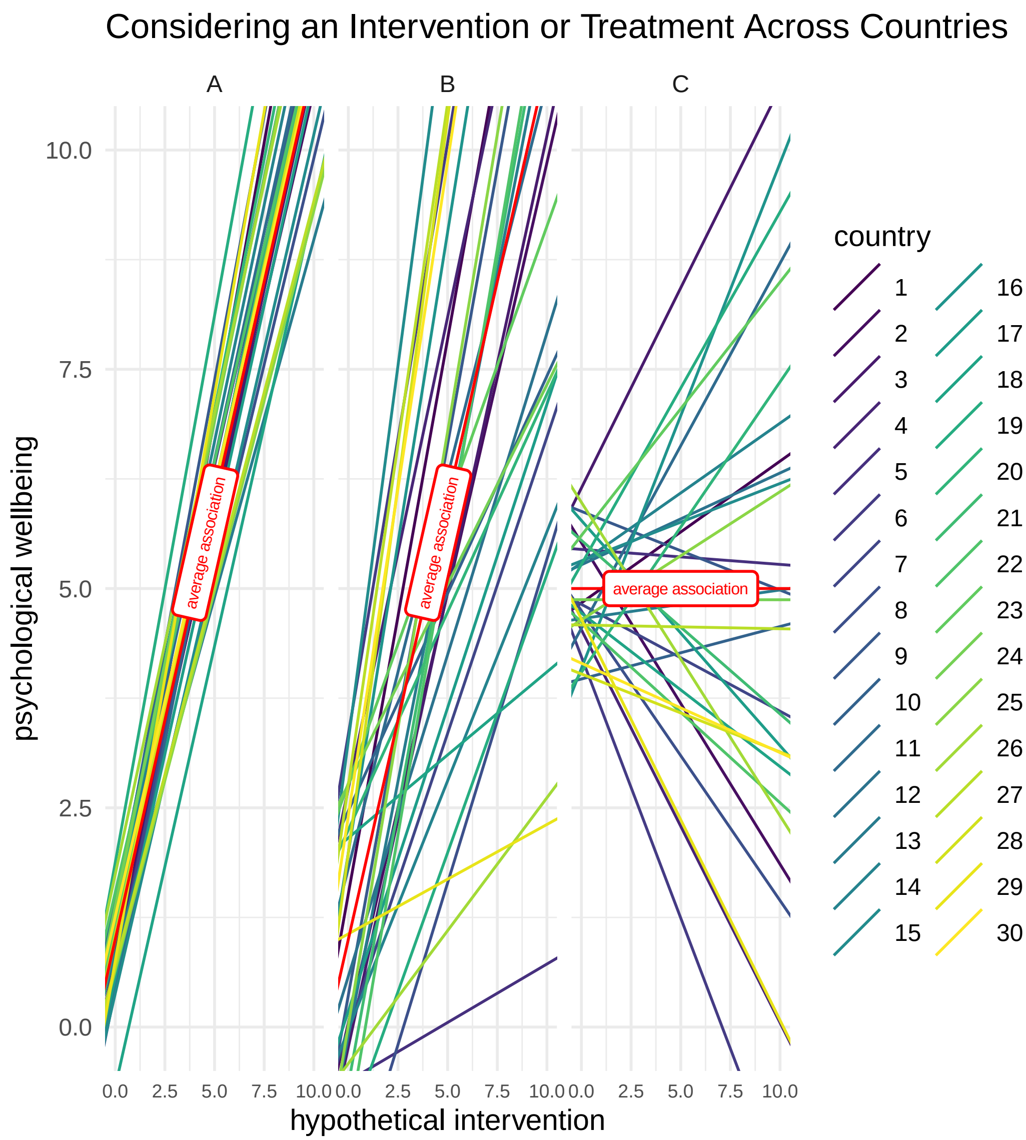

Figure 4.3: Considering an Intervention or Treatment Across Countries

trolling for variation.

> "… universal theorizing requires adequately sampled (i.e., diverse) data and better appreciation of issues of comparability and the most powerful theories ought to predict and explain variation, not sweep variation under the rug." (Blasi et al., 2022)

As I discuss these ideas in more statistical depth, later in the book, I develop more statistically based ideas about the study of diversity and variation in Section 5.4.2, Section 5.7, and Section 5.10.

Again, statistically sophisticated treatments of all of the ideas are available in one form or another across the excellent textbooks on multilevel modeling (Hox et al., 2018; Kreft & de Leeuw, 1998; Luke, 2004; Rabe-Hesketh & Skrondal, 2012; Raudenbush & Bryk, 2002; Singer & Willett, 2003; Snijders & Bosker, 2012). However, some of these ideas appear less often in applied research, and my intention here is to make the application of these ideas to applied research, and to concerns of variation and diversity, more clear.

5 The Cross Sectional Multilevel Model

> "Mathematical Science shows us what is. It is the language of unseen relations between things. But to use & apply that language we must be able fully to appreciate, to feel, to seize, the unseen, the unconscious. Imagination too shows us what is, the is that is beyond the senses." (Lovelace, 1992)

> "I'm often asked if there is something I think writers ought to do, and recently in an interview I heard myself say: 'Several things. Love words, agonize over sentences. And pay attention to the world.' " (Sontag, 2007)

5.1 Introduction

I begin this chapter with some introductory thinking about multilevel modeling, by starting with two key ideas: multilevel models can improve our estimation of p values; multilevel models can improve our estimation of β coefficients.

After introducing these two key concepts of multilevel modeling, I then begin a more in depth exploration of the equations and concepts and statistical syntax of the cross sectional multilevel model.

5.2 Some First Ideas About Multilevel Modeling

5.2.1 Estimating Standard Errors And p Values

5.2.1.1 Introducing the Idea

If the data are grouped, nested, or clustered, then this aspect of the structure of the data needs to be accounted for. Bland & Altman (1994) describe a simulation in which grouped data are artificially generated according to the following procedure.

> "The data were generated from random numbers, and there is no relation between X and Y at all. Firstly, values of X and Y were generated for each 'subject,' then a further random number was added to make the individual observation." (Bland & Altman, 1994)

The graph below illustrates the process of simulating the data.

5.2.1.2 Compare OLS and MLM

An analysis that is not aware of the grouped nature of the data will give biased results, will mis-estimate standard errors, and importantly, will often attribute statistical significance to some

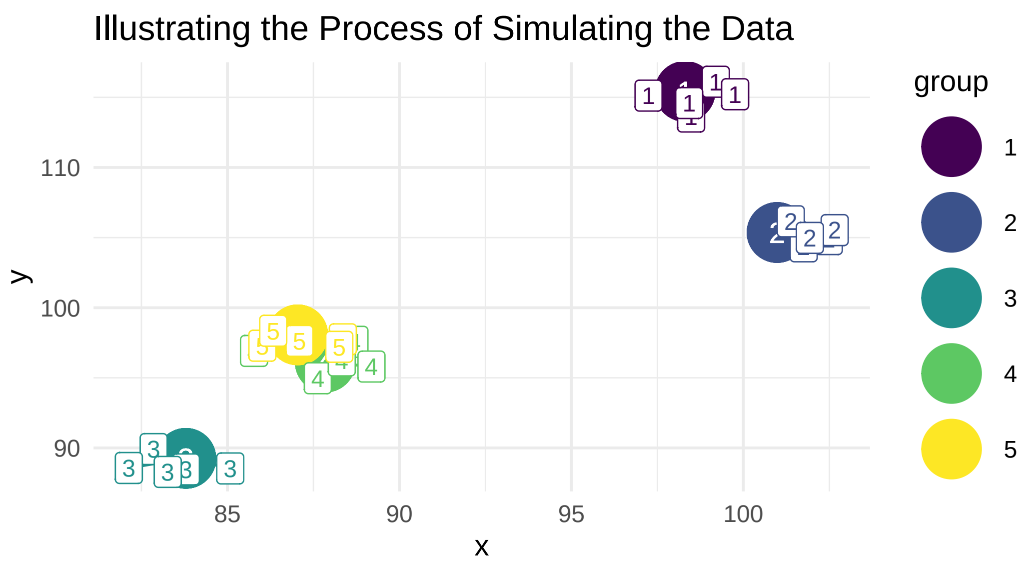

Figure 5.1: Simulated Clustered Data

of the independent variables when this is not appropriate (Bland & Altman, 1994; Raudenbush & Bryk, 2002).

In the example below, we compare a simple ordinary least squares analysis of the data with a multilevel model that accounts for the clustered nature of the data.

	OLS		MLM	
x	1.046	**	0.039	
Intercept	4.488		97.005	**
var(_cons)			74.523	
var(e)			0.594	
Number of observations	25			

** p<.01, * p<.05

We see that in the ordinary least squares analysis, the independent variable is judged to have a statistically significant association with the dependent variable. The more appropriate multilevel model finds that in fact the independent variable x is *not* associated with y. Thus, the multilevel model provides more accurate results than OLS in the presence of clustered data.

5.2.2 Multilevel Structure

Associations between two variables can be *very different* (or even *reversed*) depending upon whether or not the analysis is "aware" of the grouped, nested, or clustered nature of the data (Gelman et al., 2007). In the example presented here, the groups are countries, but could as easily be neighborhoods, communities, or schools.

> For teaching purposes, I use an example with very few clusters, although it would be more appropriate to apply multilevel analysis to an example with many more clusters e.g. ($N_{\text{clusters}} >= 30$)

A model that is "aware" of the clustered nature of the data may provide very different–likely better–substantive conclusions than a model that is not aware of the clustered nature of the data.

I use some data simulated for this particular example.

5.2.2.1 Graphs

5.2.2.1.1 A "Naive" Graph

This "naive" graph is unaware of the grouped nature of the data. Notice that the overall regression line slopes downward, even though there is some suggestion that *within each group* the regression lines may slope upward.

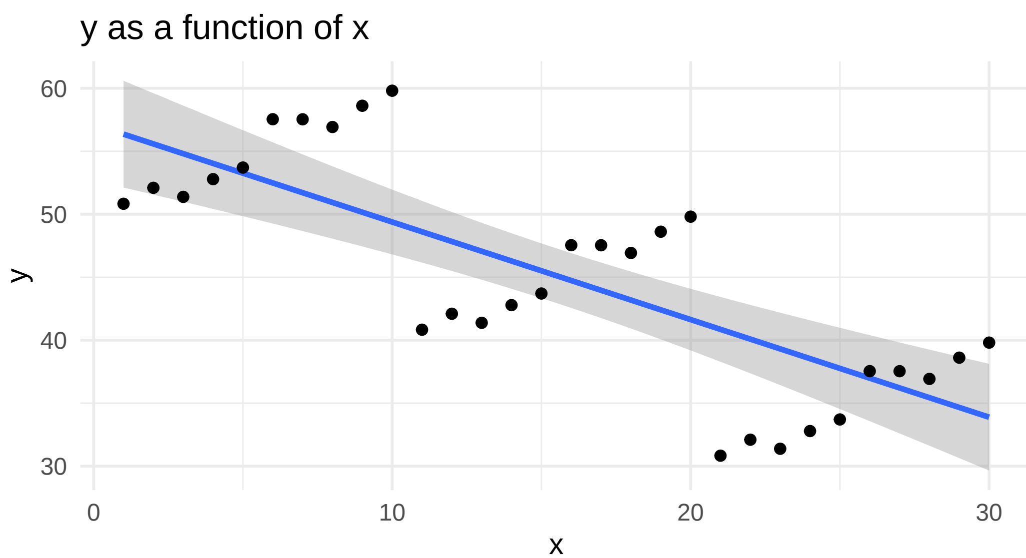

Figure 5.2: A 'Naive' Graph

5.2.2.1.2 An "Aware" Graph

This "aware" graph is aware of the grouped nature of the data. The graph is "aware" of the grouped or clustered nature of the data, and provides indication that the regression lines *when accounting for group* slope upward.

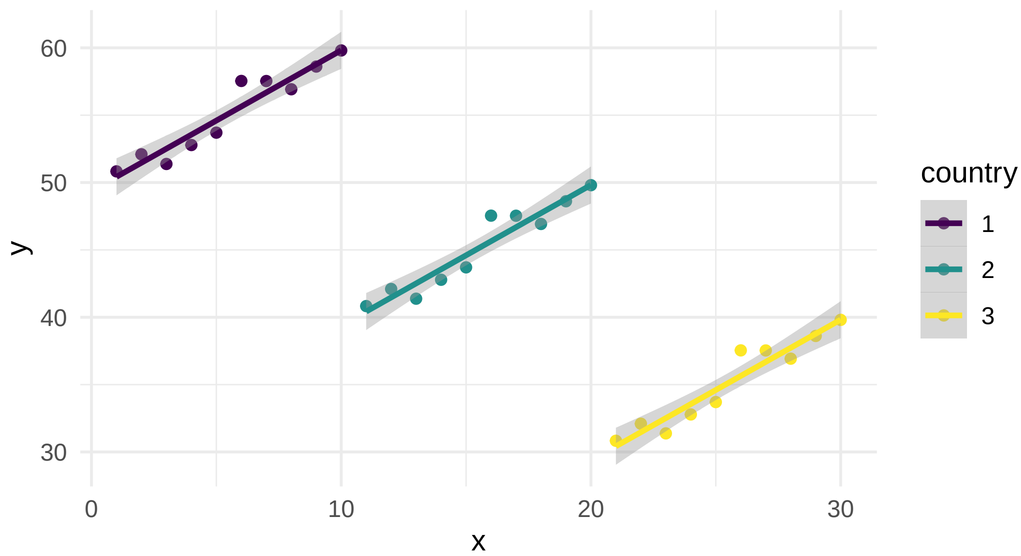

Figure 5.3: An 'Aware' Graph

5.2.2.2 Regressions: A "Naive" OLS Analysis vs. An "Aware" MLM Analysis

The OLS model with only x as a covariate is not aware of the grouped structure of the data, and the coefficient for x in the OLS model reflects this. The coefficient for x in the OLS model is *negative*, and statistically significant.

The multilevel model is aware of the grouped structure of the data, and the coefficient for x in the multilevel model reflects this. The coefficient for x in the multilevel model is *positive*, and statistically significant.

	OLS		MLM	
x	-0.775	**	1.038	**
Intercept	57.133	**	29.029	**

	OLS	MLM
var(_cons)		276.867
var(e)		0.916
Number of observations	30	

** p<.01, * p<.05

5.2.2.3 A Thought Experiment

When might a situation like this arise in practice? This is surprisingly difficult to think through.

Imagine that x is a protective factor, or an intervention or treatment. Imagine that y is a desirable outcome, like improved mental health or psychological well being.

Now imagine that residents of countries provide more of the protective factor or more of the intervention in situations where there are lower levels of the desirable outcome. If one thinks about it, this is a very plausible situation.

> A naive analysis that was unaware of the grouped nature of the data would therefore misconstrue the results, suggesting that the intervention was harmful, when it was in fact helpful.

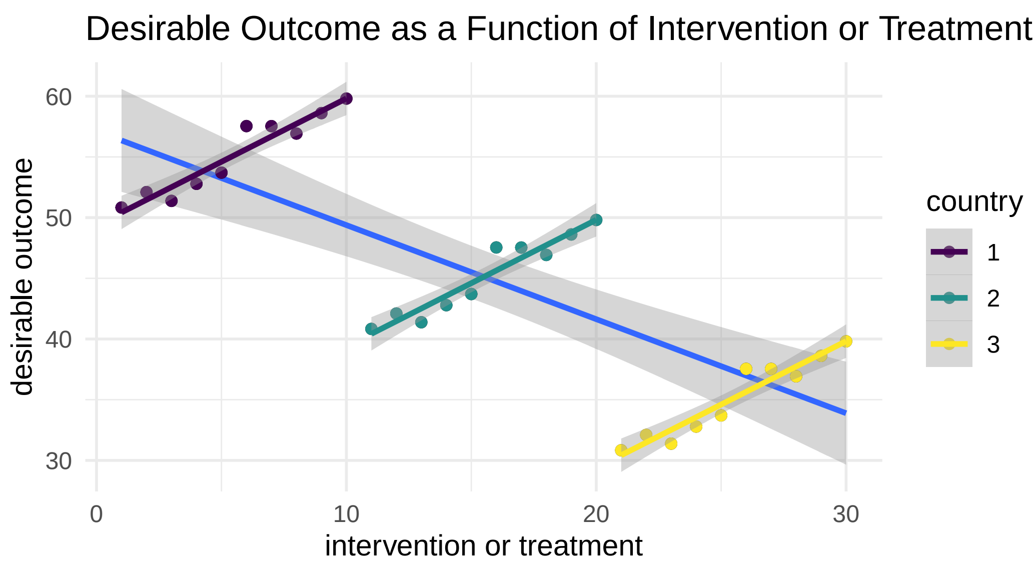

Figure 5.4: A Heuristic Example

The idea that group level and individual level relationships must be the same has been termed the "ecological fallacy" (Firebaugh, 2001; Hox et al., 2018; Snijders & Bosker, 2012).

These data are constructed to provide this kind of extreme example, but it easy to see how multilevel thinking, and multilevel analysis may provide better answers than one would get if one ignored the grouped nature of the data.

5.3 The Equation

The equation for the multilevel model can be written in several ways: as multiple levels of equations; or as a single equation. The advantage of having multiple levels of equations is that these multiple equations make clear the multiple levels of the data, and thus conform to an initial understanding of how a multilevel model should be estimated. However, *results* from multiple levels of equations quickly become difficult to interpret, and thus, I will not spend a great deal of time on discussing empirical results of the two level formulation. Whether multiple levels of equations, or a single equation are employed, the numerical results are equivalent.s

5.3.1 Two Levels of Equations

I start with two levels of equations: Level 1 at the level of the individual; and Level 2 at the level of the country.

5.3.1.1 Level 1 (Individuals)

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + \beta_{2j}z_{ij} + e_{ij} \tag{5.1}$$

5.3.1.2 Level 2 (Countries)

$$\beta_{0j} = \gamma_{00} + \gamma_{01}w_j + u_{0j} \tag{5.2}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

Here y_{ij} is the dependent variable, or outcome for the model. We note that the ij subscripts indicate that this is outcome y for individual i in country j. Note that the outcome is at Level 1, or the level of individuals. β_{0j} is a regression intercept, and the other β's[1] are regression slope parameters. x_{ij} and z_{ij} are independent variables and t_{ij} is an independent variable indicating the time at which different data points are measured. I note that in this discussion I am *not* considering a model in which there are repeated observations on the same individuals, although the multilevel model is certainly extensible to such cases. u_{0j} is a random intercept for the β_{0j} term, and u_{1j} is a random slope for the β_{1j} term, indicating that we are modeling cross country variation in these parameters. The other β terms are not modeled as having random country level variation, although this could certainly be a possibility in subsequent models.

In this formulation of the multilevel model, each regression parameter β in the level 1 equation is the outcome of an equation at Level 2. The parameters for the Level 2 equations are represented by γ's. w a Level 2 variable appears in the first Level 2 equation.

[1] Technically, all of these β's could be written as β_j since the multilevel model could be said to estimate a regression parameter for each group, in this case each country. One could even write β_{jk} to represent the regression parameter for the k^{th} independent variable the for the j^{th} group or country. To keep matters simple, I simply write β in most cases.

5.3.2 One Level of Equations

By simply substituting the values of the Level 2 equations into the Level 1 equations–and rewriting the γ's as β's–we obtain:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 z_{ij} + \beta_3 w_j + u_{0j} + u_{1j} \times x + e_{ij} \tag{5.3}$$

Here again y_{ij} is the dependent variable, or outcome for the model. β_0 is a regression intercept, and the β's are regression parameters. x_{ij} and z_{ij} are independent variables and w is a Level 2 variable.

> Notice that in this *single equation* format all variables–no matter their *level*–appear in the same equation.

In this formulation of the equation, the nature of the random effects is more clear, and merits discussion. Notice that we have included a *random intercept* u_{0j} as well as a *random slope* $u_{1j} \times x$. The *random intercept*, u_{0j}, indicates that there is variation in the *intercept* of the country specific regression lines, as is true in Figure 3.2. The *random slope* term associated with x, $u_{1j} \times x$, indicates that we are allowing for the possibility of variation in the *slope* of the regression lines that is associated with x, in this case, the slope of parental warmth, as is possibly suggested in Figure 3.2.

To make these ideas more concrete, I rewrite this equation in terms of the main substantive ideas of this book:

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth}_{ij} + \beta_2 \text{physical punishment}_{ij} + \tag{5.4}$$

$$\beta_3 \text{identity}_{ij} + \beta_4 \text{intervention}_{ij} + \beta_5 \text{HDI}_{ij} +$$

$$u_{0j} + u_{1j} \times \text{parental warmth} + e_{ij}$$

Put substantively, this model indicates that the outcome can be conceptualized as a function of an intercept term, and contributions of parental warmth, physical punishment, identity group membership, participation in the intervention, and country level HDI. The random intercept, u_{0j} indicates that there is some unexplained variation in the outcome at the country level. The random slope $u_{1j} \times$ parental warmth indicates that the model is allowing for country level variation in the association of parental warmth with the outcome. Inspection of Figure 3.2 indicates that it might be possible that there would be variation across countries in this slope. The model could be extended to allow for country level variation in other slope terms by adding other random slopes, eg u_{2j}, u_{3j}, etc.

5.4 Regression With Simulated Multi-Country Data

After considering some of these broader issues, let's now examine the results of a multilevel regression with the simulated multicountry data. I will again imagine that the desirable outcome is an outcome such as improved psychological wellbeing.

5.4.1 Unconditional Model

The unconditional model is a model with no x's or covariates (Raudenbush & Bryk, 2002).

$$\text{outcome}_{ij} = \beta_0 + u_{0j} + e_{ij} \tag{5.5}$$

Here, outcome$_{ij}$ is a function of an intercept β_0, a country specific error term, u_{0j}, and an individual level error term e_{ij}.

Thus, all of the variation in outcome$_{ij}$ is–given the *unconditional* nature of our model–attributable to unmeasured variation at the country and individual level.

5.4.2 Intra-Class Correlation Coefficient

I now introduce a measure known as the Intra-Class Correlation Coefficient, (ICC) that can be computed from this unconditional model (Raudenbush & Bryk, 2002).

$$\text{ICC} = \frac{var(u_{0j})}{var(u_{0j}) + var(e_{ij})} \tag{5.6}$$

Heuristically:

$$\text{ICC} = \frac{\text{group level variation}}{\text{group level variation} + \text{individual level variation}} = \tag{5.7}$$

$$\frac{\text{group level variation}}{\text{total variation}}$$

The ICC from the *unconditional* model (Equation 5.5) is the most informative ICC as it represents the amount of variation in the dependent variable that could *potentially* be explained by the grouping variable.

Put another way, in a two level model, the ICC provides a quantitative measure of the amount of variation in a measure that is present at Level 2. Knowing the ICC, we can then easily calculate the percentage of variation at Level 1:

$$\text{Level 1 varation} = \text{total variation} - \text{Level 2 variation} =$$

$$= 100\% - (100\% \times \text{ICC})$$

Thus, in some broader sense, the ICC might be thought of as a measure of diversity: the higher the ICC, the higher the clustering of the data in groups, and the lower the diversity within the groups; the lower the ICC, the lower the clustering of the data in groups, and the higher the diversity within groups between individuals.

	1	
_cons	52.433	**
var(_cons)	3.179	

	1
var(e)	39.461
Number of observations	3000

** p<.01, * p<.05

From using procedures to estimate the ICC, as detailed in the Appendix, or calculating by hand, we see that the ICC for this data is .076 or 7.6%.

As we add covariates, x's, to the model the ICC will most often decrease.

5.4.3 Conditional Model

We next estimate a *conditional* model, *with* independent variables.

	1	
warmth	0.835	**
physical_punishment	-0.992	**
identity		
1	-0.300	
intervention		
1	0.640	**
HDI	-0.003	

	1	
_cons	52.000	**
var(warmth)	0.023	
var(_cons)	2.964	
var(e)	34.975	
Number of observations	3000	

** p<.01, * p<.05

The data suggest that parental warmth is positively associated with the desirable outcome, and that this result is statistically significant. Parental use of physical punishment is associated with statistically significant decreases in the desirable outcome. The identity variable is not associated here with the outcome. In contrast, the application of the intervention is associated with increases in the outcome.

I note that there is some variation in the *constant* indicating that there is some variation in the initial or average levels of the desirable outcome–again improved psychological well-being–that is attributable to country.

There is–in contrast–no discernible variation in the *slope* associated with parental warmth that is attributable to country. Thus, the relationship of parental warmth with child outcomes does not appear to differ appreciably from country to country. Had there been statistically significant variation in this *random slope*, it would have indicated that the association of parental warmth with the outcome varied across countries.

`HDI`, the *Human Development Index*, our only country level, or Level 2, variable in this model is not associated with the outcome.

5.5 Indicator Variables, Random Intercepts and Random Slopes, and Identities

5.5.1 Variable Types

In thinking about any statistical analysis, it is important to think about different types of variables. Thinking about different types of variables may seem to be an arcane or obscure topic. Statisticians can make very fine distinctions between different types of variables, and it sometimes seems that there are as many typologies of variables as there are statisticians. Nonetheless some broad distinctions are useful.

In a classic text, Freedman et al. (1991) offer a short definition of variable types that provides some useful crucial distinctions:

> "Some questions are answered by giving a number: the corresponding variables are *quantitative*. Age, family size, and family income are examples of quantitative variables. Some questions are answered with adjectives, and the corresponding variables are *qualitative*: examples are marital status (single, married, widowed,

divorced, separated) and employment status (employed, unemployed, not in the labor force)."

When teaching and learning about statistical software, I find it easiest to re-label *quantitative* variables as *continuous* or *numeric* variables, and *qualitative* variables as *categorical* variables.[2]

5.5.2 Categorical Variables as Indicators or Random Intercepts

Statistically, there is often a concern about whether a particular qualitative or categorical variable is most appropriately modeled as an indicator variable, or as a level (random intercept). Substantively, this question intersects with how one should statistically include and model various measures of identity. Many identities are often measured as categorical variables.

5.5.3 The Example of U.S. Census Data

The United States Census (United States Census Bureau, 2022) asks about race using several different categories: White; Black or African American; American Indian or Alaska Native; Asian; Native Hawaiian and Pacific Islander; Some Other Race. Followup questions are asked for some identities, and a separate question is asked about Latino / Hispanic identity. Thus one might imagine a questionnaire with two measures.

[2] I recognize that there are finer distinctions to be made here, many of which Freedman et al. (1991)–as well as other introductory texts–go on to make. However, for the purposes of explication in this book, I find the *continuous/numeric* versus *categorical* variable distinction to be the most useful and the one that most readily facilitates communication with faculty colleagues and with students.

Table 5.5: Hypothetical Questions Measuring Race

Race	Latino
White	Latino or Hispanic
Black or African American	Not Latino or Hispanic
American Indian or Alaska Native	
Asian	
Native Hawaiian and Pacific Islander	
Some Other Race	

A table of data might then look something like the following.

Table 5.6: Simulated Data on Race and Ethnicity

id	outcome	race	latino	country
1	110.9	2	1	21
2	85.56	1	0	6
3	104.4	5	0	3
4	90.79	1	1	1
5	108.7	1	0	4
6	114.4	1	0	13

More recently, the Census has allowed respondents to select multiple racial identities. Such a table of data might look like this.

Table 5.7: Simulated Data on Race and Ethnicity With Multiple Identities

id	outcome	race1	race2	race3	race4	race5	race6	latino	country
1	110.9	0	0	1	0	0	0	0	19
2	85.56	0	0	1	0	0	0	0	4
3	104.4	0	0	1	0	0	1	0	24
4	90.79	0	1	1	0	0	0	1	30
5	108.7	1	0	1	1	1	0	0	19
6	114.4	1	0	0	1	0	1	0	25

5.5.4 Identities As Indicator Variables

Identities can be modeled as indicator variables. Importantly, whether only a single identity is selected (e.g. Table 5.6), or multiple identities are selected (Table 5.7), if identities are modeled as indicator variables, they should be modeled as a *set* of indicator variables with an omitted reference category. If there are k categories of a variable, there should be $k-1$ indicator variables., e.g.

$$y_{ij} = \beta_0 + \beta_2 \text{race2} + \beta_3 \text{race3} + \beta_4 \text{race4} + \beta_5 \text{race5} + \beta_6 \text{race6} + \tag{5.8}$$

$$\beta_7 \text{latinx} + u_{0j} + e_{ij}$$

In Equation 5.8 the first group of race, `race1` is treated as the reference category, and is therefore omitted from the model, and all comparisons are made to individuals with identity `race1`.

> **Identities As Indicator Variables in Equations And Syntax**
>
> Thus, if an identity, such as race, is used as an *indicator variable*, it would appear in the equations (e.g. Equation 5.4), and in the statistical syntax covered in the Appendix, in the same place as the `identity` variable.

> **Reference Categories Need To Be Chosen Carefully**
>
> Reference categories need to be chosen carefully. This is especially true in studies that hope to be attentive to diversity and social change. The default in many software programs is to exclude the first category of an identity, as is evident in Equation 5.8. However, in the example given in Table 5.5, this would mean that all comparisons would be made to individuals who identified as *white*. It often makes sense to choose a different reference category than the default, and investigators are encouraged to be thoughtful about the choice of reference category for indicator variables. In most software, the choice of reference categories can be manually specified.

⚠ Indicator Variables Should Not Be Treated As A Continuous Variable

Identities that are measured in the data with a single categorical variable with values like `1`, `2`, `3`, `4`, `5`, `6` should *not* be modeled as a single continuous variable. For example, if the data are similar to those presented in Table 5.6–where identity is measured as a single column of data–it is important that the multiple identities *not* be modeled as a single variable, which would end up *de facto* treating this multi-category *categorical* variable as a single *continuous* variable. Instead, multiple indicator variables $(k-1)$ for the multiple (k) identities should be clearly specified in one's equation (as in Equation 5.8) and in the statistical syntax. Details of how to accomplish this for different software packages are included in the Appendix.

5.5.5 Identities as Random Intercepts or Slopes

If there are many values of an identity it may be difficult to model those multiple identities as indicator variables. For example, if there were 10 possible values of a particular identity, and one was modeling those identities with indicator variables, one would need to include 9 $(k-1)$ indicator variables. Those 9 indicator variables could potentially use a large fraction of the available degrees of freedom, and interpreting the β regression coefficients for 9 indicator variables might also be challenging. The problem is even greater when one considers a larger number of identities (e.g. 25, 30, 50, 100), as is possible in some data sets. In a global or cross cultural data set, such as the simulated data that is used as an example throughout this book, one might easily conceive of data with 20, 30 or 50 different identities, especially since racial and ethnic identity categories may differ substantially across countries, around the world (Rocha & Aspinall, 2020).

An alternative would be to model large numbers of possible identities as a random intercept, rather than as a set of indicator variables. Such an equation might appear as follows:

$$y_{ij} = \beta_0 + \Sigma\beta_m \text{covariates} + v_{0k} + u_{0j} + e_{ij} \tag{5.9}$$

Here, the inclusion of v_{0k}, a random intercept for identity, would be a way to model the presence of many possible values of an identity variable.

> Identities As Random Intercepts in Equations And Syntax
>
> Thus, if an identity, such as race, is used as a *random intercept*, it would appear in the equations (e.g. Equation 5.4), and in the statistical syntax covered in the Appendix, in the same place as the `country` variable.

An *advantage* of the approach outlined in Equation 5.9 is that we could model multiple identities without including a large–potentially enormous–number of indicator variables. We would thus avoid using up a large number of degrees of freedom in our data set. We would also avoid the conceptual difficulties that might come from including a large number of indicator variables in our data set. For example, if we had 30 categories of a particular categorical variable, it might be difficult to interpret the resultant 29 regression coefficients for the 29 indicator variables. At the same time, it would be straightforward to include a random intercept that had 30, or even 50, or 100, or 1,000 possible values.

A potential *disadvantage* of the approach outlined in Equation 5.9 is that this is multi-country data that already employs a random slope, u_{0j}. Adding v_{0k} means that we now have a model with *two* random slopes, a topic which is discussed in **Chapter XXXXXXX**.

A *caveat* of the approach outlined in Equation 5.9 is that random intercepts (e.g. v_{0k} and u_{0j})–which are essentially error terms at level 2–are assumed to follow a normal distribution. Ten identities, to follow the example above, is generally considered to be too few groups to satisfy this assumption of a normal distribution. C. J. M. Maas & Hox (2004) suggest that at least 50 level 2 units are necessary to ensure satisfaction of this normality assumption. Importantly, if one has fewer than 50 units, the bias introduced only appears to affect the estimation of the level 2 random intercepts and slopes, not the estimation of the independent variables (C. J. M. Maas & Hox, 2004; C. Maas & Hox, 2005). If one has fewer than this number one possible procedure is to model the groups both as a *random intercept* and as *a set of indicator variables*, and to see if the different approaches lead to different substantive conclusions (Gershoff et al., 2010).

A second *caveat* of modeling identities as a random intercept is that these identities would need to be mutually exclusive. For example, “black”, “white” and “identifies as both black and white”, would all need to be separately coded identities under this approach.

5.6 Correlation of Random Intercept and Random Slope(s)

To further elaborate the cross-sectional multilevel model that we have been considering, we could also consider a situation in which a random slope or slopes were *correlated* with each other, and with the random intercept. In the equation that we are considering, this would entail estimation of whether or not, the random intercept, u_{0j}, was correlated with the random slope for warmth, u_{1j}.

Substantively, this question would be asking whether the association of warmth and the outcome, was correlated with the initial level or average level of the outcome. From Figure 3.2, it appears that there is some slight evidence that the country specific regression slopes are more steep in countries where the initial level of the outcome is higher. However, we may wish to investigate this question more rigorously.

Procedures for estimating models with correlated or uncorrelated random effects vary across software. I illustrate this issue in Equation 5.10 below, where the diagonal elements are the *variances* of each of the random effects, and the off diagonals, which would be the *covariances* of the random effects are constrained to 0.

$$\begin{bmatrix} var(u_{0j}) & 0 \\ 0 & var(u_{1j}) \end{bmatrix} \tag{5.10}$$

In contrast, we might wish to estimate a model in which the random effects are allowed to be correlated.

$$
\begin{bmatrix} var(u_{0j}) & cov(u_{0j}, u_{1j}) \\ cov(u_{0j}, u_{1j}) & var(u_{1j}) \end{bmatrix} \tag{5.11}
$$

When we estimate such a model, we get the following information.

	1	
warmth	0.833	**
physical_punishment	-0.994	**
identity		
1	-0.298	
intervention		
1	0.644	**
HDI	-0.008	
_cons	52.292	**
var(warmth)	0.010	
var(_cons)	2.257	
cov(warmth,_cons)	0.147	
var(e)	35.006	
Number of observations	3000	

** p<.01, * p<.05

Results are mostly similar to those above. However, here, we are asking additionally for information about the possible *correlation* of country specific initial levels of the outcome and the slope of the country specific regression line for parental warmth. Results indicate that there is no reason to be believe that these two parameters are correlated. Put more intuitively, it does not appear that parental warmth is any more or less correlated with the outcome in countries where initial levels of the outcome are higher. Again, had this correlation been statistically significant and positive, it would have indicated that higher initial, or average levels of the outcome were associated with a greater association of warmth with the outcome.

5.7 Within and Between

Coefficients in models can be divided into within and between. A substantive example may be helpful here. When we consider the variable of parental `warmth`, we can imagine the parental warmth expressed in each family, warmth_{ij}, representing family i in country j. We can also think about the *grand mean* of warmth across the entire sample, $\overline{\text{warmth}}_{..}$. We can then also think about the mean expression of parental warmth in each country, $\overline{\text{warmth}}_{.j}$, i.e. the mean level of parental warmth in country j.

Bearing this in mind, one can then think about the *difference* between each individual expression of parental warmth and the overall, or grand mean: $\text{warmth}_{ij} - \overline{\text{warmth}}_{..}$. This value can then be decomposed into two values:

$$\text{warmth}_{ij} - \overline{\text{warmth}}_{..} = \text{warmth}_{ij} - \overline{\text{warmth}}_{.j} + \overline{\text{warmth}}_{.j} - \overline{\text{warmth}}_{..}$$

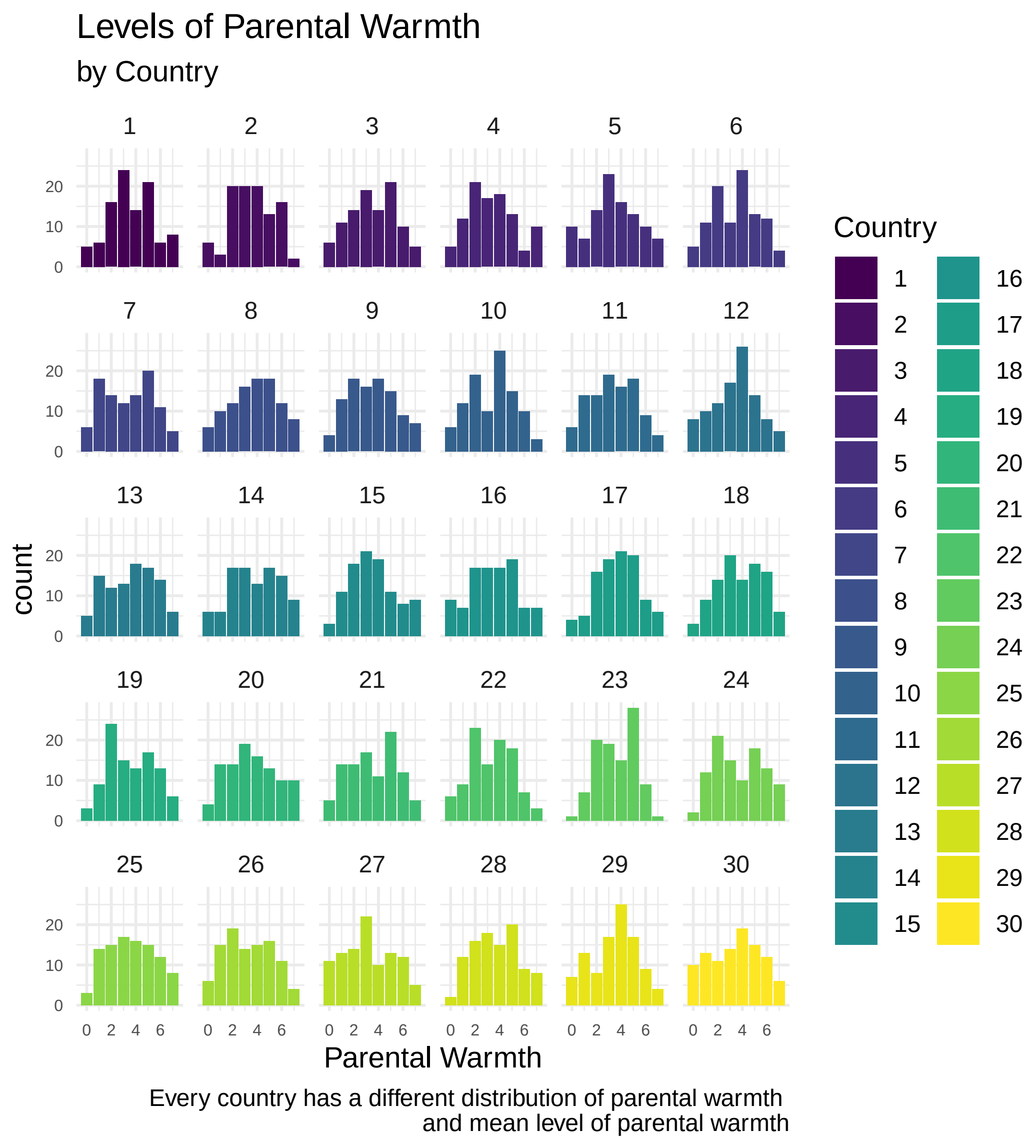

Figure 5.5: Distribution of Parental Warmth Across Countries

Put into words, this equation says that the difference in parental warmth displayed by family i in country j from the overall or grand mean of parental warmth is composed of two components:

- *Within Country Component*: How is the level of warmth expressed by family i in country j different from the *mean* level of warmth in country j. Is family i different from the *average* family in country j? For this particular country, is this a family that is higher, or lower, than average in parental warmth?
- *Between Country Component*: How is the *mean* level of warmth in country j different from the overall or *grand mean* level of warmth in the sample as a whole? To what degree is country j different from *all countries* in the sample? Is this country a country where parents tend to be higher, or lower, in parental warmth?

Theoretically, or conceptually, one might imagine that it would be useful to decompose a particular behavior into within country and between country components. The within country component could be theorized as *how an individual family differs from their context*, and the between country component could be theorized as *how a particular context differs from the average context*.

In terms of using statistical software, we need to follow a few steps.

1. Calculate the *grand mean* of the variable.
2. Calculate *country specific means* of the variable.
3. Calculate:

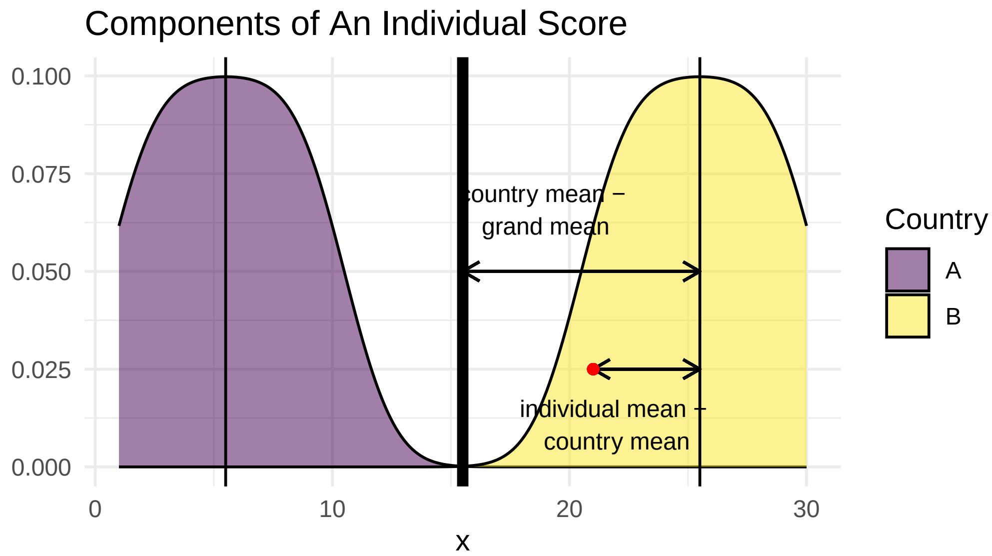

Figure 5.6: Decomposing a Variable into Within and Between Differences

- individual scores - country specific means
- country specific means - grand mean

4. Estimate the model with within and between.

	1	
dev_warmth	0.834	**
cdev_warmth	1.196	
physical_punishment	-0.992	**
identity		
1	-0.300	
intervention		
1	0.640	**

	1	
HDI	-0.004	
_cons	54.981	**
var(warmth)	0.023	
var(_cons)	2.964	
var(e)	34.975	
Number of observations	3000	

** p<.01, * p<.05

Estimates suggest that both the difference in an individual family's expression of parental warmth from the country level mean, *but not* the difference in the country level mean from the grand mean are statistically significant predictors of the outcome.

5.8 Summary of Advantages Of The Multilevel Model

The discussion so far gives an idea of the advantages of the multilevel model for studying intrinsically multilevel data: children in classrooms or schools; individuals or families in neighborhoods; individuals or families in countries. These advantages can be summarized below:

1. Standard errors are estimated correctly as is statistical significance. This means that p values are correctly estimated accounting for the clustered or nested nature of the data.

More colloquially, this most often means that we do not make the mistake of attributing statistical significance to a given risk or protective factor, when such a statistical significance is not warranted. Put even more straightforwardly correct estimation of standard errors and statistical significance prevents us from seeing results that are simply not present in the data, whether those concern risk factors or protective factors.

2. Regression coefficients are estimated correctly accounting for the clustered or nested structure of the data. If one does not account for the clustered or nested structure of the data, regression slopes can be estimated as negative when they are more correctly estimated as positive, or as null, or conversely estimated as positive when there are more correctly seen as negative (or null). Again, to phrase things in a more colloquial fashion, this means that we do not judge something to be a risk factor when it is in fact a protective factor or a null effect; or a protective factor when it is in fact a risk factor, or a null effect.

5.9 Some Wrong (or Partially Wrong) Approaches

When data are clustered–e.g. residents in neighborhoods, children in schools, families in countries–it is worth discussing the fact that we have several choices statistically as how to proceed, other than using a multilevel model. Given the discussion so far, we can see the advantages of a multilevel model over these other approaches:

1. First, we could simply ignore the clustering, and treat the data as though it were com-

posed of statistically independent individuals, i.e. statistically independent e_i. As we have discussed above, however, this approach has at least two disadvantages. First, as discussed in Section 5.2.1, this approach will mis-estimate standard errors, most often underestimating them, resulting in underestimated p values and false positives. Second, as discussed in Section 5.2.2 ignoring clustering runs the risk of estimating regression β's that are not estimated with information about the multilevel structure of the data, with the possibility that β coefficients may not only have incorrect statistical significance, but also incorrect magnitude, and even incorrect sign.

2. A second approach would be to *aggregate* the data to the level of the higher social unit, e.g. aggregating the data at the level of the neighborhood. Here we run into an idea similar to that discussed in Section 5.2.2, the "ecological fallacy": the idea that group level and individual level relationships are necessarily the same (Firebaugh, 2001).

3. Lastly, we could adopt a statistical strategy of *clustering* the standard errors. Clustering the standard errors means that standard errors are corrected for the non-independence of the e_i within clusters. Thus, p values are estimated correctly. However, clustering still does not account for the multilevel structure of the data (Section 5.2.2), and thus when relationships between x's and y at different levels of the data are very different, simply clustering the standard errors may not give correct estimates of the β's.

5.10 Variation

Above, in Section 4.3, I have referred to multilevel models as the study and exploration of variation. Now that I have provided some discussion of the multilevel model, more statistical "unpacking" of ideas about variation is warranted.

I provide again, for pedagogical purposes, the example substantive equation (Equation 5.4) that I have been using in this book.

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth}_{ij} + \beta_2 \text{physical punishment}_{ij} +$$
$$\beta_3 \text{identity}_{ij} + \beta_4 \text{intervention}_{ij} + \beta_5 \text{HDI}_{ij} +$$
$$u_{0j} + u_{1j} \times \text{parental warmth} + e_{ij} \tag{5.12}$$

5.10.1 Measured and Unmeasured Variation

An equation for a multilevel model can be divided into measured and unmeasured variation. Below I use a simplified form of Equation 5.12, focusing in particular–for sake of illustration–on the identity variable.

$$\underbrace{y_{ij}}_{\text{outcome}} = \underbrace{\beta_0}_{\text{intercept}} + \underbrace{\beta_1 x}_{\text{slope ofmeasured x}} + \underbrace{\beta_2 \text{identity}}_{\substack{\text{association of}\\ \text{measured identity}\\ \text{with intercept}}} + \underbrace{\beta_3 x \times \text{identity}}_{\substack{\text{association of}\\ \text{measured identity}\\ \text{with slope of}\\ \text{measured x}}} +$$

$$\underbrace{u_{0j}}_{\substack{\text{unmeasured}\\\text{Level 2}\\\text{variation}\\\text{in intercept}}} + \underbrace{u_{1j} \times x}_{\substack{\text{unmeasured}\\\text{Level 2}\\\text{variation}\\\text{in slope of x}}} + \underbrace{e_{ij}}_{\substack{\text{unmeasured}\\\text{individual}\\\text{error}}}$$

I have already introduced the idea of an unconditional model (Section 5.4.1), in which there are no independent variables, and all of the variation is unmeasured. The unconditional intraclcass correlation coefficient (ICC) (Section 5.4.2) is a measure of the amount of variation that could potentially be attributable to the Level 2 units, in this case, different countries.

5.10.2 Variation In Intercepts or Outcomes

In Equation 5.12, $var(u_{0j})$ is the model estimated amount of variation in the *outcome*, y_{ij}.

In the regression in Section 5.4, there is discernible between country variation, but more of the variation is between individuals within the same country. Put another way, there is a moderate tendency for children in families in the same country to have similar outcomes, but two children in families in the same country may also have very different outcomes. Children from families in different countries may be as similar as children from families in the same country.

5.10.3 Variation In Predictors

Equally important, I think, but much less frequently explored than variation in *outcomes*, is the possibility of variation in *predictors*, $var(x_{ij})$. In the substantive example that we have

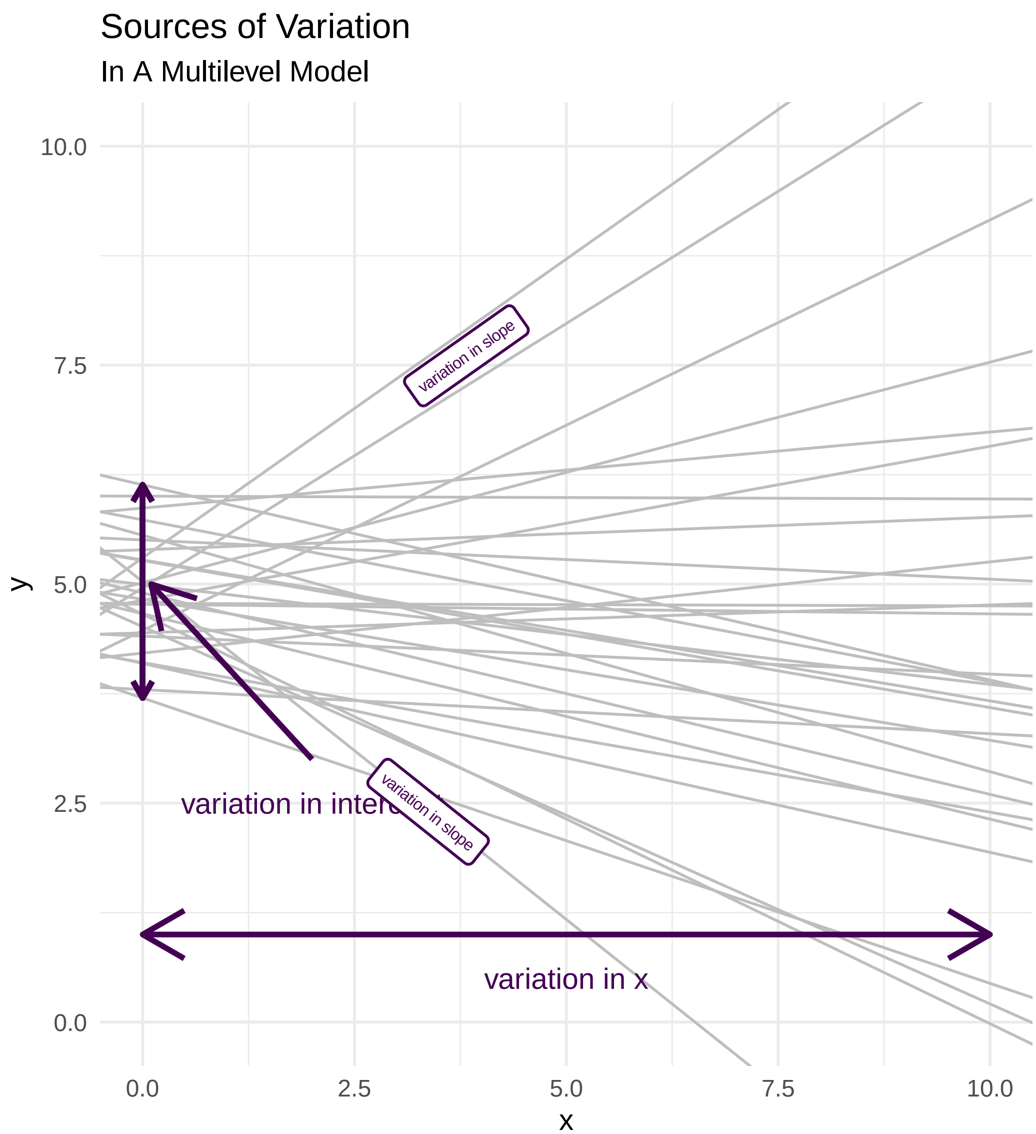

Figure 5.7: Sources of Variation in a Multilevel Model

employed so far, the *predictors* are different *parenting behaviors*, so considering variation in *predictors* allows us to consider variation in *parenting behaviors*, as well as variation in the *outcomes* of those behaviors.

We would estimate variation in behaviors attributable to country in much the same way that we would estimate variation in outcomes, estimating an unconditional model, but substituting x for y.[3]

$$x_{ij} = \beta_0 + w_{0j} + e_{ij} \tag{5.13}$$

Then, similarly, the variation in a predictor attributable to the clustered nature of the data–in this case the clustering of individuals in countries–is given by:

$$\text{ICC}_x = \frac{var(w_{0j})}{var(w_{0j}) + var(e_{ij})} \tag{5.14}$$

5.10.4 Variation in Slopes

Another possible type of variation to investigate is variation in the relationship of x and y, which is represented in the multilevel model by examining variation in the β's, i.e. $var(u_{1j})$.

[3]Here for the sake of clarity, I use w_{0j} as a random effect to think about country specific variation in x.

5.10.5 Summary

Thus, we can consider a number of sources of possible variation.

Table 5.10: Some Possible Sources of Variation To Consider in A Multilevel Model

Model Parameter	Meaning
Independent Variables	
$var(x_{ij})$	What is the variation in x?
$range(x_{ij})$	What are the maximum and minimum of x?
$var(w_{0j})$ if $x = \beta_0 + w_{0j} + e_{ij}$	What is the country specific variation in the value of x?
Dependent Variable	
$var(y_{ij})$	What is the variation in y?
$range(y_{ij})$	What are the maximum and minimum of y?
$var(u_{0j})$	What is the country specific variation in the intercept of y?
Regression Coefficients for Slopes	
$\beta_x x$	What is the relationship of x and y?
$\beta_{xz} z \times x$	What is the effect of z on the relationship of x and y?

Model Parameter	Meaning
$var(u_{1j})$ from $u_{1j} \times x$	What is the country specific variation in the relationship of x and y?
$cov(u_{0j}, u_{1j})$	What is the covariance of the country specific intercept and and country specific slope. Is the country specific intercept related to the country specific slope?

5.10.6 Variation As An Outcome

Even less common is to examine *variation* itself as an outcome (Burkner, 2018).

$$\sigma_{yij} = \beta_0 + \beta_1 x_1 + u_{0j} + e_{ij} \tag{5.15}$$

Here, the variation in the outcome, σ_{yij}, rather than the mean level of the outcome, y_{ij}, is the focus of interest. My notation for Equation 5.15 draws upon Burkner (2018)'s notation, but is modified in order to be consistent with the rest of this book.

Why might such models be of conceptual interest? Imagine for example, that the *variation* in psychological well-being is higher in countries with higher levels of poverty, or higher levels of income inequality. The use of such models as this, discussed in more detail by Burkner (2018), would allow us to explore such a question.

Of note, while I do not explore in detail differences between Bayesian and frequentist approaches to multilevel modeling in this book, these models are likely to be only estimable with Bayesian software rather than with frequentist software (Burkner, 2018).

5.10.7 Maximal Models

Hypothetically, one might imagine that there could be group level unobserved factors which affect regression slopes: i.e. the relationship between a predictor x and outcome variable y. Arguably, were one to ignore these unobserved factors in statistical estimation, they would show up either in an error term, or in the regression coefficients themselves. Were they to show up in the regression coefficients this would represent statistical bias and a substantive mis-estimation of important effects. thus, there is a conceptual argument for including as many random effects—i.e. random slopes—in a statistical model as possible.

Models with all possible random effects are termed *maximal models* (Barr et al., 2013; Frank, 2018). Such models include a large number of random slopes, e.g. $u_1 \times x_1, u_2 \times x_2, u_3 \times x_3, ...,$ etc. even when some of those estimated slopes are close to 0. Such models may be more easily estimable when using Bayesian estimation (Frank, 2018), a topic which I do not cover in detail in this book.

It should be noted that Matuschek et al. (2017) argue that such a *maximal* approach may lead to a loss of statistical power and further argue that one should adhere to “a random effect structure that is supported by the data.” In contrast, Nalborczyk et al. (2019) argue that maximal models are supported under the Bayesian approach. Oberauer (2022) also argues for including multiple random slopes. Schielzeth & Forstmeier (2009) make a similar argument from a frequentist perspective.

6 The Longitudinal Multilevel Model

> "Mathematics is the art of giving the same name to different things." (Poincare, 1908)

Counter-intuitively, and surprisingly, the mathematics of estimating models with cross-sectional clustered data easily generalizes to longitudinal data. In cross sectional clustered data, we imagine *individuals or families clustered in neighborhoods, schools, or countries.*

Table 6.1: Levels in Cross-Sectional Data

Level	Example(s)
1	Individuals or Families
2	Schools
	Neighborhoods
	Countries

In longitudinal data, we consider the *first level* to be that of *time points*, or *study waves*, which we sometimes call the *person-observation*.[1] The *second level* is then the individual or family.

Table 6.2: Levels in Longitudinal Data

Level	Example(s)
1	Timepoints
2	Individuals or Families

While it is less common, we could then easily add additional clustering to this longitudinal model, for example, clustering of individuals or families inside social units.

Table 6.3: Multiple Levels in Longitudinal Data

Level	Example(s)
1	Timepoints
2	Individuals or Families
3	Schools
	Neighborhoods
	Countries

[1]When we are studying families, e.g. a parent-child pair, it might be more appropriate to call each row of data a *family-observation*, but the term *person-observation* is more commonly used.

6.1 Use Data With Multiple Observations Per Individual

Multilevel data suitable for longitudinal analysis has *multiple rows of data per individual or family*. Put another way, *every row of data is a person-timepoint*.

> This method of organizing data is known as the *long* format. Another way of organizing longitudinal data–which I do not discuss in detail here–is the *wide* format in which every individual or family has only a single row of data. In *wide* data, the different timepoints are in *different columns* of data. I do discuss *reshaping* data from *wide* to *long*, and vice versa, in the Appendix.

Table 6.4: Data in Long Format

id	t	x
1	1	10
1	2	20
1	3	30
2	1	20
2	2	30
2	3	40

Table 6.5: Data in Wide Format

id	x1	x2	x3
1	10	20	30
2	20	30	40

6.2 Simulated Multilevel Longitudinal Data

For the discussion below, I use a longitudinal version of the simulated data that has multiple rows of data per family.

Table 6.6: Simulated Longitudinal Multilevel Data

Table 6.6: Table continues below

country	HDI	family	id	identity	intervention	t
1	69	1	1.1	1	0	1
1	69	1	1.1	1	0	2
1	69	1	1.1	1	0	3
1	69	2	1.2	1	1	1
1	69	2	1.2	1	1	2
1	69	2	1.2	1	1	3

Table 6.7: Simulated Longitudinal Multilevel Data

physical_punishment	warmth	outcome
3	3	57.47
3	4	55.06
1	2	58.77
2	1	50.1
3	0	53.31
3	1	49.79

Since I will be discussing the estimation of a *longitudinal* model, it is often useful to graph the outcome variable against time.

6.3 The Equation

When data are in *long* format, the following equation is applicable. Observe that the model below is a *three level* model where *timepoints* are nested inside *families* which in turn are nested inside *countries*. A simpler two level model with *timepoints* nested inside *families* would also be possible to estimate.

$$\text{outcome}_{itj} = \beta_0 + \beta_1 \text{parental warmth}_{itj} + \beta_2 \text{physical punishment}_{itj} + \beta_3 \text{time}_{itj} + \quad (6.1)$$

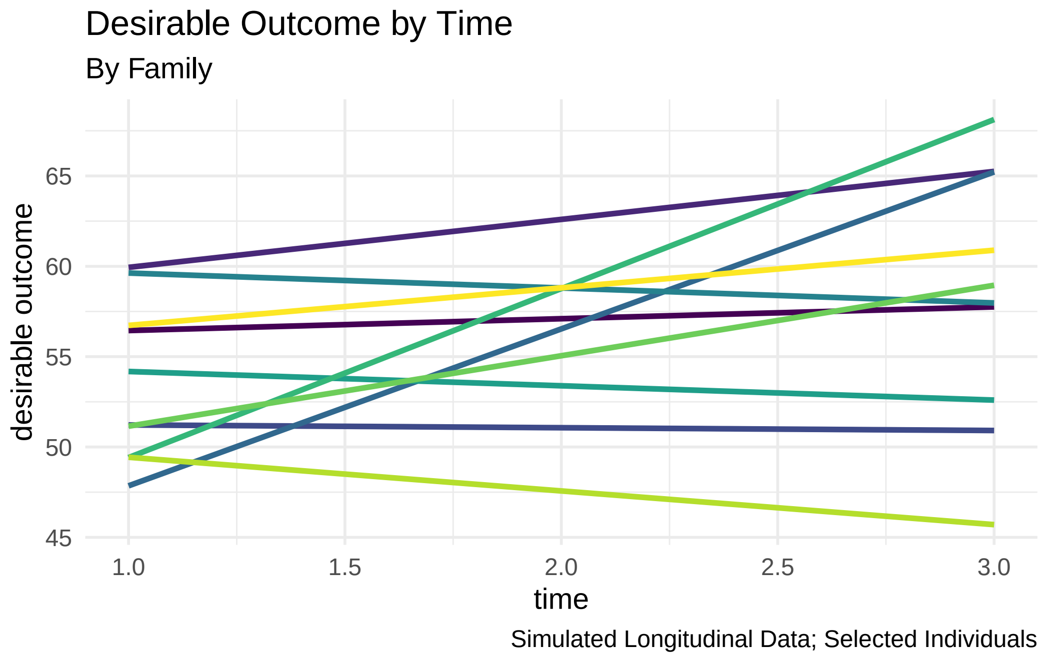

Figure 6.1: Graph of Simulated Longitudinal Data

$$\beta_4 \text{identity}_{itj} + \beta_5 \text{intervention}_{itj} + \beta_6 \text{HDI}_{itj} +$$

$$u_{0j} + u_{1j} \times \text{parental warmth}_{itj} +$$

$$v_{0i} + v_{1i} \times \text{time}_{itj} + e_{itj}$$

Here I include a random slope (u_{1j}) at the country level for parental warmth, as well as a random slope (v_{1i}) at the family level for time.

As before, the random slope for parental warmth, $u_{1j} \times \text{parental warmth}_{ij}$ suggests allows us to estimate whether the relationship between parental warmth and the outcome varies across countries. The random slope for time, $v_{1i} \times t$, allows us to estimate whether time trajectories (the slope for time) vary across families.

6.4 Growth Trajectories

In longitudinal multilevel models, the variable for *time* assumes a special role as we are often visualizing a *growth trajectory* over the course of time.

Imagine a model as follows where *identity* is a (1/0) variable for membership in one of two groups:

$$\text{outcome} = \beta_0 + \beta_t \text{time} + \beta_{\text{identity}} \text{identity} + \beta_{\text{interaction}} \text{identity} \times \text{time} + u_{0i} + e_{it}$$

Then, each identity group has its own intercept and time trajectory:

Table 6.8: Slope and Intercept for Each Group

Group	Intercept	Slope (Time Trajectory)
0	β_0	β_t
1	$\beta_0 + \beta_{\text{identity}}$	$\beta_t + \beta_{\text{interaction}}$

Thus, in longitudinal multilevel models, *main effects* modify the *intercept* of the time trajectory, while *interactions with time*, modify the *slope* of the time trajectory.

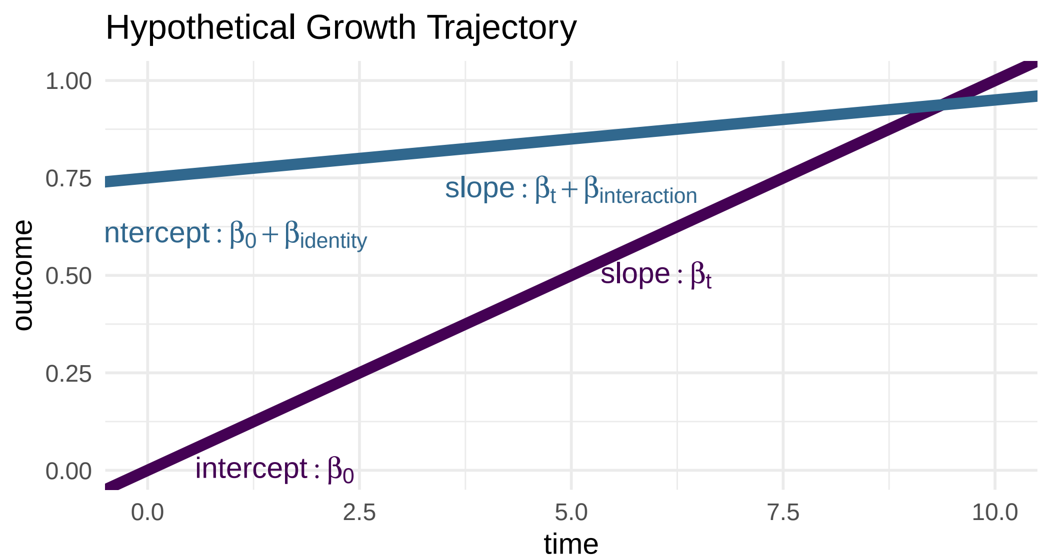

Figure 6.2: Hypothetical Growth Trajectory

6.5 Regression With Simulated Multi-Country Longitudinal Data

	1	
t	0.944	**
warmth	0.913	**
physical_punishment	-1.008	**
identity		
1	-0.128	
intervention		

	1	
1	0.859	**
HDI	-0.001	
_cons	50.467	**
var(warmth)	0.011	
var(_cons)	3.167	
var(_cons)	8.387	
var(t)	0.000	
var(e)	26.027	
Number of observations	9000	

** p<.01, * p<.05

Examining the regression results, the results of the model suggest that child outcomes improve over time. Better child outcomes are again associated with parental `warmth`, and parental use of `physical_punishment` is associated with reduced child outcomes. `identity` is not associated with the outcome. However, the `intervention` is associated with increases in the outcome. `HDI` is again not associated with outcomes.

6.5.1 Interactions With Time

As discussed in Section 6.4, we will likely wish to model not only associations of other independent variables with the intercept of the time trajectory, but also associations of other independent variables with the slope of the time trajectory. Accordingly, we modify Equation 6.2 so that it includes these interactions. Below, I add the letter B to some β coefficients to denote that they are a second coefficient estimating the *interaction* of that variable with time.

$$\text{outcome}_{itj} = \beta_0 + \beta_1 \text{parental warmth}_{itj} + \beta_2 \text{physical punishment}_{itj} + \beta_3 \text{time}_{itj} + \tag{6.2}$$

$$\beta_{1B} \text{parental warmth}_{itj} \times \text{time}_{itj} + \beta_{2B} \text{physical punishment}_{itj} \times \text{time}_{itj} +$$

$$\beta_4 \text{identity}_{itj} + \beta_5 \text{intervention}_{itj} + \beta_6 \text{HDI}_{itj} +$$

$$\beta_{4B} \text{identity}_{itj} \times \text{time}_{itj} + \beta_{5B} \text{intervention}_{itj} \times \text{time}_{itj} + \beta_{6B} \text{HDI}_{itj} \times \text{time}_{itj} +$$

$$u_{0j} + u_{1j} \times \text{parental warmth}_{itj} +$$

$$v_{0i} + v_{1i} \times \text{time}_{itj} + e_{itj}$$

	1	
t	0.758	*
warmth	0.817	**
physical_punishment	-1.009	**
identity		
1	-0.239	
intervention		
1	0.661	*
HDI	0.001	
t # warmth	0.048	
t # physical_punishment	0.001	
identity # t		
1	0.055	
intervention # t		
1	0.099	
t # HDI	-0.001	
_cons	50.836	**
var(warmth)	0.011	

	1
var(_cons)	3.170
var(_cons)	8.392
var(t)	0.000
var(e)	26.016
Number of observations	9000

** p<.01, * p<.05

Examining the regression results, the results of the model again suggest that child outcomes improve over time. Better child outcomes are again associated with parental `warmth`, and parental use of `physical_punishment` is associated with reduced child outcomes. `identity` is again not associated with outcomes, while participation in the `intervention` is associated with improvements in outcomes. `HDI` is again not associated with outcomes.

Examining the interaction terms, we find that none of these variables modify the time trajectory of the outcome.

Interactions And Random Slopes in Longitudinal Models

Having now discussed both *random slopes* (Section 5.4.3), and *interaction terms* (Section 6.5.1) in longitudinal models–and having seen that both *random slopes* and *interaction terms* involve changes in slope–one might again ask what is the difference between including a variable as a random slope or as an interaction term. When a variable is included as an *interaction term*, it indicates that we are attempting to estimate the change in slope associated with a *measured* variable. When we include a variable as a *random slope*, it indicates that we are attempting to estimate the change in slope associated with *unmeasured* variables. See in this regard Section 5.10.1

6.6 Autocorrelation

When data are ordered by a time variable t, it is possible that observations that are closer together in time will have a higher correlation than observations that are distant in time. In the simplest example, $e_{i,t=k}$ may be correlated with $e_{i,t=k-1}$. This phenomenon is known as *autocorrelation*. As Hooper (2022) would suggest, it may make sense to assume that the correlation between observations "decays with increasing separation in time".

Most software programs for multilevel modeling allow one to incorporate measures of autocorrelation so that, e.g., $e_{i,t=3}$ is allowed to be correlated with $e_{i,t=2}$, which in turn can be correlated with $e_{i,t=1}$. More complex autocorrelation structures are usually also possible (StataCorp, 2021a).

6.7 Causal Inference

6.7.1 The Importance of Causal Reasoning

Causal reasoning is sometimes considered to be a statistical–or even overly technical–concern. Arguably, however, whenever one is using research to make recommendations about *interventions*, or *treatments*, or *policies*, one is engaging in some form of causal reasoning (Duncan & Gibson-Davis, 2006).

> If one is saying that implementing x would result in beneficial changes in y, one is arguing–at least implicitly–that x is one of the causes of y.

It then behooves one to be explicit about this chain of causal reasoning. For example, to continue one of the substantive examples of this book, if one is going to argue for programs, interventions, or treatments that promote *parental warmth*, or that discourage parental use of *physical punishment* with the aim of improving children's *mental health*, one must be at least reasonably sure that *parental warmth* and *physical punishment* are *causes* of children's mental health.

In a statement salient for social research, Duncan & Gibson-Davis (2006) point out the logical inconsistency of writing that does not rigorously address causal processes, but then goes on to suggest interventions or treatment or policies:

> "Developmental studies are usually careful to point out when their data do not come from a randomized experiment. As with much of the nonexperimental litera-

ture in developmental psychology, most of the articles then go on to assert that, as a consequence, it is impossible to draw causal inferences from the analysis. Indeed, much of their language describing results is couched in terms of 'associations' between child care quality and child outcomes. It is not uncommon, however, to see these papers make explicit statements about effects, and others draw explicit policy conclusions. For instance, NICHD (1997, 876) stated, 'The interaction analyses provided evidence that high-quality child care served a compensatory function for children whose maternal care was lacking.' On the policy side, NICHD (2002c, 199) asserted, 'These findings provide empirical support for policies that improve state regulations for caregiver training and child-staff ratios.' " (Duncan & Gibson-Davis, 2006)

"One cannot have it both ways. Studies that do not aspire to causal analysis should make no claim whatsoever about effects and draw no policy conclusions. At the same time, it would be a terrible waste of resources to conduct expensive longitudinal studies without attempting to use them for causal modeling." (Duncan & Gibson-Davis, 2006)

6.7.2 Randomized Controlled Trials

Randomized studies provide the best evidence about *internal validity* and causal relationships. However, randomized studies have certain important limitations (Diener et al., 2022). First of all–especially in a study with a smaller sample–randomization may not always be perfect, and the control and treatment groups may not be statistically equivalent. Secondly, because randomized studies are costly to conduct, they may have small samples and may be statistically underpowered. Smaller samples and underpowered studies are more likely to generate false positive results than larger samples (Button et al., 2013) [2]. Further, and importantly, because of ethical concerns some studies can not be conducted with randomization (Diener et al., 2022). For example, in the study of parenting and child development, children cannot ethically be assigned to parents with different styles of parenting and followed over the long term (Heilmann et al., 2021). Finally, and crucially, because of their often small samples, and their often rigorous exclusion criteria, randomized studies may have high internal validity, but much lower external validity, or generalization to larger populations (Diener et al., 2022). This issue of generalizability becomes increasingly salient, when we are reminded of the fact that so little social and psychological research has been conducted outside of North American contexts (Draper et al., 2022; Henrich et al., 2010). Thus, methods that provide rigorous causal estimation with observational methods are necessary (Diener et al., 2022).

6.7.3 Observational Studies and Causality

Because of the assumed superiority of studies that employ randomization, it is sometimes maintained that *correlation is not causation* and that studies that do not make use of randomization are *only observational* and *correlational*, and that results from observational studies cannot be used to support causal conclusions. However, in important reviews Waddington et al. (2022)

[2] See https://agrogan.shinyapps.io/Thinking-Through-Bayes/ for a demonstration of this idea from a Bayesian perspective.

and Dahabreh & Bibbins-Domingo (2024) suggest that studies using appropriately quantitative methods can provide causally robust conclusions. Heilmann et al. (2021) make a similar assertion with specific regard to studies of physical punishment and child outcomes, arguing that observational studies that make use of appropriately advanced quantitative methods can make causally robust conclusions about the effects of physical discipline.

It is necessary to make use of broadly representative observational data sets, and appropriately sophisticated quantitative methods, to make causally robust conclusions from observational data that are applicable across diverse populations.

6.7.4 Formal Criteria of Causality

For x to be a cause of y, one needs the following 3 things to be true (Holland, 1986).

1. x is (are) associated with (correlated with) y.
2. x come(s) before y in time.
3. z–or other factors–cannot explain the association of (correlation of) x and y.

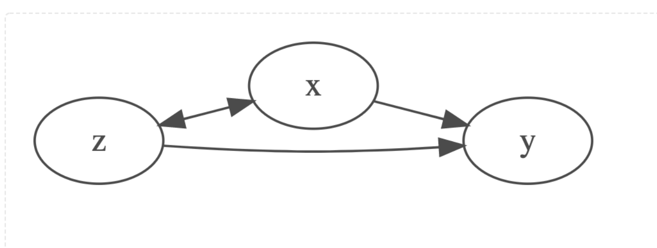

Figure 6.3: Formal Criteria of Causality

If z is omitted from the regression model, then the estimates for $x \to y$ (i.e. $\beta_{x \to y}$)

will be biased. In a common scenario, $\beta_{x \to y}$ may be an over-estimate of the effect, and statistical significance of $\beta_{x \to y}$ may represent a false positive.

It is likely useful to restate the above abstract statements in terms of the substantive issues that I have been considering so far in this book.

For *parenting* to be a cause of *child outcomes*, one needs the following 3 things to be true (Holland, 1986).

1. *parenting* is (are) associated with (correlated with) *child outcomes*.
2. *parenting* come(s) before *child outcomes* in time.
3. *SES*, *community characteristics*–or other factors–cannot explain the association of (correlation of) *parenting* and *child outcomes*.

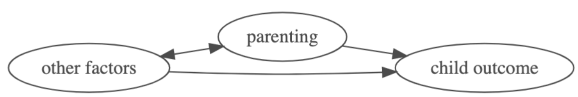

Figure 6.4: Formal Criteria of Causality: A Substantive Example

If *other factors* are omitted from the regression model, then the estimates for parenting $\to$ child outcome (i.e. $\beta_{\text{parenting} \to \text{child outcome}}$) will be biased. In a common scenario, $\beta_{\text{parenting} \to \text{child outcome}}$ may be an over-estimate of the effect, and statistical significance of $\beta_{\text{parenting} \to \text{child outcome}}$ may represent a false positive.

6.7.5 Simpson's Paradox

Earlier, in Section 5.2.2, I referred to the idea of *multilevel structure* wherein failure to account for the clustering of data–omission of u_0 from the equation being estimated–may lead to incorrect conclusions. A closely related phenomenon is that of *Simpson's Paradox* (Simpson, 1951) wherein omission of a relevant *covariate* (e.g. z_{it} such as SES, community characteristics, country level characteristics) may also lead to dramatically incorrect results. The issue of omitted variables is a crucially important–and sometimes underappreciated–issue that pervades all statistical work.

Statistically, we imagine a situation where the true model is:

$$\text{child outcome}_{it} = \beta_0 + \beta_1 \text{parenting}_{it} +$$

$$\beta_2 \text{individual or family or community or country characteristic}_{it} +$$

$$u_{0i} + e_{it}$$

If *individual or family or community or country characteristics* in fact influence *outcome*, but are not included in the statistical model, perhaps because they are not measured in the data, then the estimate of β_1 for *parenting* will be biased. See Figure 6.5 for an illustration. When possible confounders are *measured*, we can include those variables in the statistical model.

When possible confounders are *unmeasured*, we need to try to use methods that capture those *unmeasured* confounders.

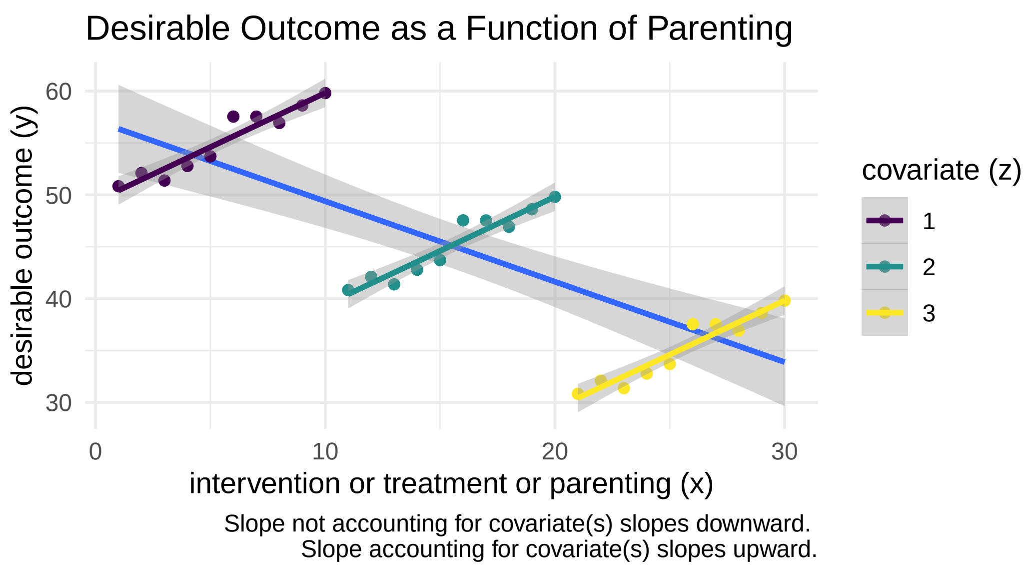

Figure 6.5: An Illustration of Simpson's Paradox

6.7.6 A Simpler Multilevel Model To Explore Causality

For purposes of explication of ideas about causal estimation, in this section, I imagine a simpler equation where I am only considering the clustering of *person timepoints* within *individual people*, and ignoring for the moment–again for the sake of exposition–the clustering of *individuals* within *countries*.

After explication and comprehension of this model, however, it is a simple matter to add back in the random effects for country level clustering.

The appropriate multilevel model is below.

$$\text{outcome}_{it} = \beta_0 + \beta_1 \text{parental warmth}_{it} + \beta_2 \text{physical punishment}_{it} + \beta_3 \text{time}_{it} + \tag{6.3}$$

$$\beta_4 \text{identity}_{it} + \beta_5 \text{intervention}_{it} + \beta_6 \text{HDI}_{it} +$$

$$v_{0i} + e_{it}$$

Note that in Equation 6.3, if one were estimating a *multilevel model*, one would consider the v_{0i} to be a randomly varying parameter with a mean of 0, and a variance of $\sigma^2(v_{0i})$.

6.7.7 Fixed Effects Regression

I can use the same equation:

$$\text{outcome}_{it} = \beta_0 + \beta_1 \text{parental warmth}_{it} + \beta_2 \text{physical punishment}_{it} + \beta_3 \text{time}_{it} + \tag{6.4}$$

$$\beta_4 \text{identity}_{it} + \beta_5 \text{intervention}_{it} + \beta_6 \text{HDI}_{it} +$$

$$v_{0i} + e_{it}$$

However, in Equation 6.4, I now consider the v_{0i} to be *estimable* for each individual i in the data. In effect, the v_{0i} become a unique indicator variable for each individual in the data set. This is known as a *fixed effects regression model.*

Recall the discussion in Section 5.7. In essence, in the fixed effects regression model, I am only making use of the variation within individuals, and not making use of the variation between individuals.

Details are provided in Allison (2009) and Wooldridge (2010). StataCorp (2021b) provides an exceptionally clear explication of the core idea of fixed effects regression. The essential idea is that the fixed effects model provides statistical control for all time invariant characteristics of study participants, such as–as is often the case in many data sets–their racial or ethnic identity, their neighborhood of residence, or other characteristics which by definition are time invariant, such as the region of the country or city in which a respondent was born. Importantly, (Ma et al., 2018) note that:

> "Another potential omitted variable is that of genetic predisposition, in that observed neighborhood effects on child outcomes are possibly attributable to a genetic heritage shared by parents and their child (Caspi et al., 2000)."

Such genetic heritage could be considered to be a time invariant variable that, while unobserved, would be controlled for by a fixed effects regression.

Thus, by ruling out many potential confounds, fixed effects regression methods provide much more causally robust analyses, specifically because they control for many more possible confounding variables than do standard regression methods, including multilevel models, which are only able to control for the variables that are measured in the study *and* that are included within the regression model.

However, a disadvantage of the fixed effects approach is that this approach can not provide estimates for any time invariant characteristic of study participants. Indeed, if one includes time invariant variables into a fixed effects regression, they are automatically dropped from the regression results as can be seen in the regression table below.

	MLM		FE	
t	0.943	**	0.944	**
warmth	0.913	**	0.916	**
physical_punishment	-0.982	**	-1.094	**
identity				
1	-0.116			
intervention				
1	0.886	**		
HDI	0.001			
_cons	50.298	**	50.988	**
var(_cons)	11.831			
var(e)	26.033			
Number of observations	9000		9000	

** $p<.01$, * $p<.05$

In comparing the multilevel model and the fixed effects regression, we note a few salient difference. First, the fixed effects are similar to the multilevel model coefficients. (Most often, the fixed effect regression coefficients are attenuated versions of the multilevel model coefficients, but not always.) The fixed effects regression coefficients for variables that have some variation over time, provide estimates that control for all time invariant variables in the model.

Second, estimates for any quantities that do not vary over time, in this case, `identity` group membership, participation in the `intervention`, and `HDI`, are not available from the fixed effects regression.

6.7.8 The Correlated Random Effects Model

The *correlated random effects* model is based upon ideas first developed by Mundlak (1978) and later explicated in Wooldridge (2010). Antonakis et al. (2021) and Schunck (2013) provide very intuitive explanations of this model.

The central idea is that one can obtain estimates of both the time invariant variables, and estimates for time varying variables. The key idea is that for time varying variables, I include the *individual* level mean for that variable in the model. Thus, in the example below, I include $\beta_{1a}\overline{\text{parental warmth}}_i$ and $\beta_{2a}\overline{\text{physical punishment}}_i$. [3] This is similar in approach to what is

[3] The correlated random effects model can also be applied cross-sectionally, but the model is much easier to explicate in the longitudinal context.

described in Section 5.7, however, here I am simply adding the group level mean to the equation instead of decomposing independent variables into within and between components.

$$\text{outcome}_{it} = \beta_0 + \beta_1 \text{parental warmth}_{it} + \beta_{1a} \overline{\text{parental warmth}}_i + \tag{6.5}$$

$$\beta_2 \text{physical punishment}_{it} + \beta_{2a} \overline{\text{physical punishment}}_i +$$

$$\beta_3 \text{time}_{it} +$$

$$\beta_4 \text{identity}_{it} + \beta_5 \text{intervention}_{it} + \beta_6 \text{HDI}_{it} +$$

$$v_{0i} + e_{ij}$$

By including these parameters, I obtain estimates for the time varying variables that are *equivalent* to what I would obtain from a fixed effects regression (Schunck, 2013).

	MLM		FE		CRE	
t	0.943	**	0.944	**	0.944	**
warmth	0.913	**	0.916	**	0.916	**

	MLM		FE		CRE	
physical_punishment	-0.982	**	-1.094	**	-1.094	**
identity						
1	-0.116				-0.116	
intervention						
1	0.886	**			0.890	**
HDI	0.001				0.001	
mean_warmth					-0.005	
mean_physicalpunishment					0.192	
_cons	50.298	**	50.988	**	50.086	**
var(_cons)	11.831					
var(e)	26.033				26.024	
var(_cons)					11.824	
Number of observations	9000		9000		9000	

** p<.01, * p<.05

Note a couple of things from this table. First, results from the correlated random effects model, and the fixed effects regression model are exactly the same for *time varying* variables, `t`, `warmth`, and `physical_punishment`. Again, these coefficients for *time varying* variables are estimated with statistical control for all time invariant characteristics of study subjects, whether those characteristics are observed, or unobserved. Secondly, unlike the fixed effects regression, coefficients for *time invariant* variables, e.g. `identity` group, participation in the `intervention`, `HDI`, mean levels of `warmth`, and mean levels of `physical_punishment`, are provided, while they would not not provided in the fixed effects model.

7 Conclusion

> "We have peered into a new world and have seen that it is more mysterious and more complex than we had imagined." (Rubin, 1997)

> "To take on a new perspective obviously does not mean throwing out all of our knowledge; what it supposes, rather, is that we will relativize that knowledge and critically revise it from the perspective of the popular majorities. Only then will the theories and models show their validity or deficiency, their utility or lack thereof, the universality or provincialism. Only then will the techniques we have learned display their liberating potential or their seeds of subjugation." (Martin-Baro, 1994b)

Many data sets relevant to the study of important social issues, or social problems, are inherently multilevel. For example, data on diverse children in schools, diverse individuals in neighborhoods, and individuals or families in diverse and different countries all have multi-level structures in which individuals are clustered in higher level social structures. Data with repeated measures, sometimes termed panel data, can also be thought of as multilevel data sets, wherein individual timepoints are nested inside individuals, who may in turn be nested or clustered in larger social units such as countries.

Failure to use appropriate basic multilevel models with such multilevel data can lead to answers that are either biased, or demonstrably wrong. Simple multilevel models allow the researcher to correctly estimate statistical significance, and to correctly estimate regression coefficients while accounting for multilevel structure. More advanced applications of multilevel models allow the researcher to explore the variation in both predictors and outcomes–and the relationship of predictors to outcomes–and to characterize the extent of this variation. Lastly, multilevel models provide a foundation for thinking about closely related models–fixed effects regression, and correlated random effects models–that provide methods for estimation that afford stronger causal conclusions.

Thus, for applied researchers, interested in addressing a variety of social problems and social issues with diverse samples of individuals, multilevel models present a method to think clearly about variation, to explore that variation, and to extend that thinking about variation to estimate more causally robust models within the context of diversity and variation.

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8 About the Author

I am the Sandra K. Danziger Collegiate Professor of Social Work at the University of Michigan School of Social Work.

My interests are in developing more knowledge to reduce violence against children and Adverse Childhood Experiences (ACEs), with the aim of improving child and family well-being. It is my hope that a better understanding of how to reduce violence against children, and how to reduce ACEs, will contribute to a better understanding of how to improve mental health and well-being across the lifespan. In this research I try to understand the family and community origins of aggression, antisocial behavior, anxiety and depression across diverse communities and contexts. My current research focuses on parenting and child development using international data. I try to understand these issues within the context of current conversations about children's rights.

A particular focus of my work has been to examine the outcomes of physical punishment. Working closely with many colleagues, we have shown that physical punishment is associated with a wide variety of negative outcomes. This finding remains true even in contexts when physical punishment is used minimally, or when used in ostensibly “normative” ways. We have investigated these associations across diverse communities and countries. Lastly, we have worked to demonstrate more “causally robust” associations between physical punishment and undesirable child outcomes using a variety of quantitative methods.

A more recent stream of research examines a broader range of parenting behaviors, with particular emphasis on “positive parenting” strategies.

I teach courses mostly in the area of statistics, quantitative methods and data visualization.

A Reshaping Data in Stata

A.1 Introduction

Data can be reshaped from *wide* format to *long* format, and back again. Almost any software that is capable of estimating multilevel models is capable of reshaping data. The Stata command for reshaping data is `reshape`.

Below, I detail the procedure for reshaping data in Stata. Here is a sample of the longitudinal data set used in this book.

These data are in *long* format (see Table 6.4).

> Every individual in the data has multiple rows. Every row of the data is a *person-timepoint*.

Table A.1: Data in Long Format

Table A.1: Table continues below

country	HDI	family	id	identity	intervention	t
1	69	1	1.1	1	0	1
1	69	1	1.1	1	0	2
1	69	1	1.1	1	0	3
1	69	2	1.2	1	1	1
1	69	2	1.2	1	1	2
1	69	2	1.2	1	1	3

Table A.2: Data in Long Format

physical_punishment	warmth	outcome
3	3	57.47
3	4	55.06
1	2	58.77
2	1	50.1
3	0	53.31
3	1	49.79

A.2 Data Management

1. Because `reshape`-ing your data dramatically changes the structure of your data, it is a good idea to have your raw data saved in a location where it will not be changed, and can be retrieved again if the `reshape` command does not work correctly, or if you simply want to modify your `reshape`-ing data workflow.
2. Usually we want to work with only a subset of your data, so keep only the data in which you are interested. In Stata, the command to keep only variables of interest would be `keep y x z t`.

A.3 Reshaping Data From Long To Wide

While it is not often that we want to reshape data from *long* to *wide*, I do so here for illustrative purposes. The Stata command for reshaping the data to *wide* format is:

```
reshape wide physical_punishment warmth outcome, i(id) j(t)
```

Notice that I only list variables that vary over time, or are *time varying*. Stata assumes that variables that are not listed do not vary over time, or are *time invariant*.

The data are now in *wide* format (See Table 6.5).

> Every individual in the data set has a single row of data. Every row in the data set is an individual.

Table A.3: Data in Wide Format

Table A.3: Table continues below

id	physical_punishment1	warmth1	outcome1	physical_punishment2
1.1	2	3	59.18	2
1.10	3	1	52.09	3
1.100	1	4	49.3	0
1.11	2	3	61.99	2
1.12	3	4	47.45	3
1.13	5	3	61.11	3

Table A.4: Data in Wide Format

Table A.4: Table continues below

warmth2	outcome2	physical_punishment3	warmth3	outcome3	country	HDI
2	58.29	3	3	60.58	1	69
2	52.99	2	1	64.37	1	69
4	64	2	4	57.34	1	69
5	55.91	2	4	65.44	1	69
4	46.42	5	6	48.35	1	69
4	56.99	3	4	50.63	1	69

Table A.5: Data in Wide Format

family	group
1	2
10	2
100	2
11	2
12	1
13	1

A.4 Reshaping Data From Wide To Long

Usually, we are more interested in reshaping data from *wide* to *long*, and that is what I do now.

Notice again that I only list variables that vary over time, or are *time varying*. As before, Stata assumes that variables that are not listed do not vary over time, or are *time invariant*.

Notice also that our *time varying* data are in the *stub-time* format, e.g. `warmth1`, `warmth2`, `physical_punishment1` `physical_punishment2`, etc. Because the variables are named in this way, Stata knows to use the *stub* (e.g. `warmth`) as the variable name, and the numeric value, (e.g. 1, 2, 3) as the timepoint.

The command is:

```
reshape long physical_punishment warmth outcome, i(id) j(t)
```

> The `id` variable, whatever it is named, has to uniquely identify the observations. A useful Stata command here is `isid`, e.g. `isid id`. If your `id` variable is not unique, it is often due to missing values. `drop if id == .` usually solves the problem (assuming that your `id` variable is indeed named `id`, and not something else).

If we use this command, we are back to the original format of the data set.

Table A.6: Data in Long Format

Table A.6: Table continues below

country	HDI	family	id	identity	intervention	t
1	69	1	1.1	1	0	1
1	69	1	1.1	1	0	2
1	69	1	1.1	1	0	3
1	69	2	1.2	1	1	1
1	69	2	1.2	1	1	2
1	69	2	1.2	1	1	3

Table A.7: Data in Long Format

physical_punishment	warmth	outcome
3	3	57.47
3	4	55.06
1	2	58.77
2	1	50.1
3	0	53.31
3	1	49.79

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