MULTILEVEL ANALYSIS IN THE STUDY OF CRIME AND JUSTICE

"The most pervasive fallacy of philosophic thinking goes back to neglect of context"

(John Dewey, 1931)

Neither criminal behavior nor society's reaction to it occurs in a social vacuum – for this reason criminology as a discipline is inherently a multilevel enterprise. Individual criminal behavior is influenced by larger social, political and environmental factors, as are the decisions of various actors in the criminal justice system. Classroom and school characteristics affect adolescent development, misconduct and delinquency (Beaver et al. 2008; Osgood and Anderson, 2004; Stewart, 2003). Family and neighborhood characteristics influence the likelihood of victimization and offending as well as post-release recidivism and fear of crime (Nieuwbeerta et al., 2008; Wilcox et al., 2007; Lauritsen and Schaum, 2004; Kubrin and Stewart, 2006; Wyant, 2008; Lee and Ulmer, 2000). Police department, precinct and neighborhood factors affect police arrest practices, use of force and clearance rates (Smith, 1986; Sun et al. 2008; Lawton, 2007; Pare et al. 2007; Eitle et al. 2005; Terrill and Reisig, 2003). Judge characteristics and court contexts affect individual punishment decisions (Britt, 2000; Ulmer and Johnson, 2004; Johnson, 2006; Wooldredge, 2007) and prison environments are tied to inmate misconduct, substance use and violence (Camp et al. 2003; Gillespie 2005; Huebner, 2003; Wooldredge et al. 2001). Although these examples cover a diverse array of criminological topics, they all share a common analytical quality – each involves data that are measured across multiple units of analysis. When this is the case, multilevel models offer a useful statistical approach for studying diverse issues in crime and justice. As Table 1 demonstrates, recent years have witnessed an abundance of multilevel studies across a variety of topics in criminology and criminal justice.

This chapter provides a basic introduction to the use of multilevel statistical models in the field. It begins with a conceptual overview explaining what multilevel models are and why they are necessary. It then provides a statistical overview of basic multilevel models, illustrating their application using punishment data from federal district courts. The chapter concludes with a discussion of advanced applications and common concerns that arise in the context of multilevel research endeavors.

CONCEPTUAL OVERVIEW

Multilevel statistical models are necessitated by t e fact t at social relations ips exist at several different levels of analysis t at jointly influence outcomes of interest. Smaller units of analysis are often “nested” wit in one or more larger units of analysis. For instance, students are nested wit in classrooms and sc ools, offenders and victims are bot nested wit in family and neighbor ood environments, and criminal justice personnel are nested wit in larger community and organizational contexts. In eac of t ese cases, t e c aracteristics of some larger context are expected to influence individual be avior. T is logic can be extended to any situation involving multiple levels of analysis including but not limited to individuals, groups, social networks, neighbor oods, communities, counties, states and even countries. Moreover, longitudinal researc questions often involve multilevel data structures, wit repeated measures nested wit in individuals or wit observations nested over time (e.g. Horney et al. 1995; Slocum et al. 2005; Rosenfeld et al. 2007). Ot er common applications of multilevel analysis include twin studies wit paired or clustered sibling dyads (e.g. Wrig t et al. 2008; Taylor et al. 2002) and meta-analyses t at involve multiple effect sizes nested wit in t e same study or dataset (e.g. Raudenbus , 1984; Goldstein et al. 2000). Regardless of t e level of aggregation or “nesting,” t oug , t e important point is t at criminological enterprises often involve data t at span multiple levels of analysis. In fact, given t e complexity of our social world, it can be difficult to identify topics of criminological interest t at are not c aracterized by multiple sp eres of social influence. W en t ese multiple influences are present, multilevel statistical models represent a useful and even necessary tool for analyzing a broad variety of criminological researc questions.

A MODEL BY ANY OTHER NAME?

Given t e complexity surrounding multilevel models, it is useful to distinguis up front w at can sometimes be a confusing and inexact argot. Various monikers are used to describe multilevel statistical models (e.g. multilevel models, ierarc ical models, nested models, mixed models). Alt oug t is nomenclature is often applied interc angeably, t ere can be subtle but important differences in t ese designations. Multilevel modeling is used ere as a broad, all-encompassing rubric for statistical models t at are explicitly designed to analyze and infer relations ips for more t an one level of analysis.[1] T e language of multilevel models is furt er complicated by t e fact t at t ere are various different software packages t at can be used to estimate multilevel models, some of w ic are general statistical packages (e.g. SAS, STATA) and ot ers t at are specialized multilevel programs (e.g. HLM, MLwin, aML).[2]

Additional confusion may derive from t e fact t at sc olars often use terminology suc as ecological, aggregate and contextual effects interc angeably despite important differences in t eir meaning. *Ecological effects*, or group-level effects, can refer to any group level influence t at is associated wit t e ig er level of analysis. Group level effects can take several forms. First, *aggregate effects* (sometime referred to as *nalytical* or *derived* variables) are created by aggregating individual level c aracteristics up to t e group level of analysis (e.g. percent male in a sc ool). T ese are sometimes distinguis ed from *structural effects* t at are also derived from individual data but capture relational measures among members wit in a group (e.g. density of friends ip networks) (see Luke, 2004: 6). To complicate matters, w en individual level data are aggregated to t e group level t ey can exert two distinct types of influence – first, t ey can exert *compositional effects* w ic reflect group differences t at are attributable to variability in t e constitution of t e groups – between-group differences may simply reflect t e fact t at groups are made up of different types of individuals. Second t ey can exert *contextual effects* w ic represent influences above and beyond differences t at exist in group composition. Contextual effects are sometimes referred to as *emergent properties* because t e collective exerts a synergistic influence t at is unique to t e group aggregation and w ic is not present in t e individual

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[1] Hierarc ical or nested models, for instance, tec nically refer to data structures involving exact nesting of smaller levels of analysis wit in larger units. Multilevel data, owever, can also be non-nested, or "cross-classified", in ways t at do not follow a neat ierarc ical ordering. Data mig t be nested wit in years and wit in states at t e same time, for example, wit no clear ierarc y to "year" and "state" as levels of analysis (Gelman and Hill, 2007: 2). Similarly, adolescents mig t be nested wit in sc ools and neig bor oods wit students from the same neig bor ood attending different sc ools. Althoug these cases clearly involve multilevel data, they are not ierarc ical in a tec nical sense. Similarly, "mixed models" tec nically refer to statistical models containing both "fixed" and "random" effects. Alt oug t is often is the case in multilevel models, it is not necessarily the case, so the broader rubric multilevel modeling is preferred to capture the variety of models designed to incorporate data across multiple units of analysis.

[2] A useful and detailed review of the strengths and limitations of numerous software programs t at provide for the estimation of multilevel models is provided by t e Centre for Multlevel Modeling at the University of Bristol at http://www.cmm.bris.ac.uk/learning-training/multilevel-m-software/index.shtml.

constituent parts.[3] Although the term "contextual effect" is sometimes used as a broader rubric for any group level influence, the narrower definition provided here is often useful for distinguishing among types of ecological influences that can be examined in multilevel models. Finally, *global effects* refer to structural characteristics of the collective itself that are not derived from individual data but rather reflect measures that are specific to the group (e.g. physical dilapidation of the school). These and other commonly used terms in multilevel analysis are summarized in Table 2.[4]

Theoretical Rationales for Multilevel Models

The need for multilevel statistical models is firmly rooted in both theoretical and methodological rationales. Multilevel models are extensions of traditional regression models that account for the structuring of data across aggregate groupings, that is, they explicitly account for the nested nature of data across multiple levels of analysis. Because our social world is inherently multilevel, theoretical perspectives that incorporate multiple levels of influence in the study of crime and justice are bound to improve our ability to explain both individual criminal behavior and society's reaction to it.

Figure 1 presents a schematic of a hypothetical study examining the influence of low self-control on delinquency in a sample of high school students. Imagine that self-control is measured at multiple time points for the same sample of students. In that case, multiple measures of self-control would be nested within individual students, and individual students would be nested within classrooms which are nested within schools. The lowest level of analysis would be within-individual observations of self-control, and the highest level of analysis would be school-level characteristics. Ignoring this hierarchical data structuring, then, is likely to introduce omitted variable bias of a large-scale theoretical nature.

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[3] Philosophical discourse on emergent properties dates all the way back to Aristotle but was perhaps most lucidly applied by John Stuart Mill. He argued that the human body in its entirety produces something uniquely greater than its singular organic parts, stating that "To whatever degree we might imagine our knowledge of the properties of the several ingredients of a living body to be extended and perfected, it is certain that no mere summing up of the separate actions of those elements will ever amount to the action of the living body itself" (Mill, 1843). Contextual effects models have long been applied in sociology and related fields (e.g. Firebaugh, 1978; Blalock, 1984), but these applications differ from multilevel models in that the latter are more general formulations that specifically account for residual correlation within groups and explicitly provide for examination of the causes of between-group variation in outcomes.

[4] Table 2 is partially adapted from Diez Roux (2002) which contains a more detailed and elaborate glossary of many of these terms.

Moreover, many t eoretical perspectives explicitly argue t at micro-level influences will vary across macro-social contexts. For instance, racial group t reat t eories (Blumer, 1958; Liska, 1992) predict t at t e exercise of formal social control will vary in concert wit large or growing minority populations. Testing t eoretical models t at explicitly incorporate variation in micro-effects across macro-t eoretical contexts t erefore offers an important opportunity to advance criminological knowledge. Assuming t at t eoretical influences operate at a single level of analysis is likely to provide a simplistic and incomplete portrayal of t e complex criminological social world.

Moreover, inferential problems can emerge w en data are used to draw statistical conclusions across levels of analysis. For instance, in is classic study of immigrant literacy, Robinson (1950) examined t e correlation between aggregate literacy rates and t e proportion of t e population t at was immigrant at t e state level. He found a substantial positive correlation between percent immigrant and t e literacy rate (r=.53). Yet w en individual level data on immigration and literacy were separately examined, t e correlation reversed and became negative (r=-.11). Alt oug individual immigrants ad lower literacy, t ey tended to settle in states wit ig native literacy rates t us confounding t e individual and aggregate relations ips. T is offers an example of t e *ecological fallacy*, or erroneous conclusions involving individual relations ips t at are inferred from aggregate data. As Peter Blau (1960: 179) suggested, aggregate studies are limited because t ey cannot “separate t e consequences of social conditions from t ose of t e individual's own c aracteristics for is be avior, because ecological data do not furnis information about individuals except in t e aggregate.”

T e same mistake in statistical inference can occur in t e opposite direction. T e *tomistic (or individualistic*) *fallacy* occurs w en aggregate relations ips are mistakenly inferred from individual level data. Because associations between two variables at t e individual level may differ from associations for analogous variables at a ig er level of aggregation, aggregate relations ips cannot be reliably inferred from individual level data. For instance, social disorganization t eory would predict t at crimes rates across neighbor oods are related to mobility rates because ig population turnover reduces informal social control at t e neighbor ood level. Because t is prediction refers to neighbor oods as t e unit of analysis, though, one would risk serious inferential error testing this group-level hypothesis with individual level data. For instance, one could not test the theory by examining whether or not individuals who move residences have higher criminal involvement. To do so would be to commit the atomistic fallacy. This reflects the fact that variables aggregated up from individual level data often have unique and independent *contextual* effects. Moving to a new residence represents a different causal pathway than living in a neighborhood with high rates of residential mobility.[5]

Because of the inherent difficulties in making statistical inferences across different levels of analysis, a preferred approach is to use multilevel analytic procedures to simultaneously incorporate individual and group level causal processes. Multilevel models explicitly provide for this type of statistical analysis. The difficulty is in distinguishing among the different types of individual and ecological influences that are of theoretical interest and then specifying the statistical model to properly estimate these effects.

MULTILEVEL MODELING AND HYPOTHESIS TESTING

There are also persuasive statistical reasons for engaging in multilevel modeling, such as providing improved parameter estimates, corrected standard errors, and conducting more accurate statistical significance tests. Utilizing traditional regression models for multilevel data presents several problems. Figure 2 presents a second example of hierarchical data where individual criminal offenders are nested within judges and county courts. Because several offenders are sentenced by the same judge and several judges share the same courtroom environment, statistical dependencies are likely to arise among clustered observations. When individual data is nested within aggregate groups, observations within clusters are likely to share unaccounted-for similarities. If, for instance, some judges are "hanging judges" while others are "bleeding-heart liberals," then offenders sentenced by the former will have sentences that are systematically harsher than offenders sentenced by the latter. Statistically speaking, the

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[5] Two related but distinct problems of causal inference are the *psychologistic fallacy*, which can occur when individual level data are used to draw inferences without accounting for confounding ecological influences, and the *sociologistic fallacy* which may arise from the failure to consider individual level characteristics when drawing inferences about the causes of group variability. The pyschologistic fallacy results from a failure to adequately consider *contextual effects*, whereas the sociologistic fallacy results from a failure to capture *compositional effects*.

residual errors will be correlated, systematically falling above t e regression line for t e first judge and below it for t e second. Because one of t e assumptions of ordinary regression models is t at residual errors are independent, suc systematic clustering would violate t is core model assumption. T e consequence of t is violation is t at standard errors will be *underestimated* by t e ordinary regression model. Statistical significance tests will t erefore be too liberal, risking Type I inferential errors in w ic t e null ypot esis is falsely rejected even w en true in t e population. Multilevel statistical models are needed to account for statistical dependencies t at occur among clusters of ierarc ically organized data.[6]

A related problem is t at statistical signifiance tests in ordinary regression models utilize t e wrong degrees of freedom for ecological predictors in t e model. Traditional regression models fail to account for t e fact t at ierarc ically structured data are c aracterized by different sample sizes at eac level of analysis. For example, wit data on 1,000 students nested wit in 50 sc ools, t ere would be an individual level sample size of 1,000 observations but a sc ool level sample size of only 50 observations. T is means t at statistical significance tests for sc ool-level predictors need to be based on degrees of freedom t at reflect t e number of sc ools in t e data, not t e number of students. Statistical significance tests in ordinary regression models fail to recognize t is important distinction. T e consequence is t at t e amount of statistical power available for testing sc ool-level predictors will be exaggerated. T e number of degrees of freedom for statistical significance tests needs to be adjusted for t e number of aggregate units in t e data – multilevel models provide t ese adjustments.

A t ird advantage of multilevel models over ordinary regression models is t at t ey allow for t e modeling of eterogeneity in regression effects. T e single-level regression model assumes *de facto* t at individual predictors exert t e same effect in eac aggregate grouping. Multilevel models, on t e ot er and, explicitly allow for variation in t e effects of individual predictors across ig er levels of analysis.

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[6] A simpler alternative to t e full multilevel model is to estimate an ordinary regression using robust standard errors that are adjusted for the clustering of observations across level 2 units. For example, STATA provides a "cluster" command option that adjusts standard errors for residual dependency. T is can be a useful approac w en the goal is simply to "control" for clustering, but beyond t at it does not provide the same advantages of the multilevel model. Another option is to control for group-level variation using a "fixed effects" model that includes dummy variables for eac level 2 unit in the data. T is is a useful approac for removing t e intraclass correlation due to group dependency, but it precludes examination of between-group differences.

Ulmer and Bradley, (2006), for instance, ave argued t at t e effect of trial conviction on criminal sentence varies across courts. T is proposition is illustrated in Figure 3 using federal punis ment data for a random sample of 8 districts courts. T e ordinary regression model would constrain t e effect of trial conviction to be uniform across courts, but Figure 3 clearly suggests variation in t is effect across courts. Multilevel analysis allows for t is type of variation to be explicitly incorporated into t e statistical model, providing t e researc er wit a useful tool for better capturing t e real-world complexity t at is likely to c aracterize individual influences across criminological contexts.

Ot er advantages t at also c aracterize multilevel models are t at t ey provide for convenient and accurate tests of cross-level interactions, or moderating effects t at involve bot individual and ecological variables. For example, t e influence of individual socioeconomic status on delinquency mig t depend on t e socioeconomic composition of t e sc ool. T is conditional relations ip could be directly investigated by specifying a cross-level interaction between an individual's SES and t e mean SES at t e sc ool level.

One final statistical advantage of multilevel models is t at t ey are able to simultaneously incorporate information bot wit in and between groups in order to provide optimally-weig ted group level estimates. T is is accomplis ed by combining information from t e group itself wit information from ot er similar groups in t e data, and it is particularly useful w en some groups ave relatively few observations. Because groups wit smaller sample sizes will ave less reliable group means, some regression to t e overall grand mean is expected. Utilizing a Bayesian estimation approac , t e multilevel model s ifts t e wit in group mean toward t e mean for ot er groups. T e more reliable t e group mean, t e more eavily it is weig ted; t e less reliable (and t e less variability across groups), t e more t e estimate is s ifted toward t e overall grand mean for all groups in t e data. T us estimates for specific groups are based not only on t eir own wit in-group data, but also on data from ot er groups. T is process is sometimes referred to as "borrowing power" because wit in-group estimates benefit from information on ot er groups, and t e estimates t emselves are sometimes called "s rinkage estimates" because t ey "s rink" individual group means toward t e grand mean for all groups. T e end result is t at group level estimates are optimally weig ted to reflect information bot wit in and between groups in t e data.[7]

Multilevel models, t en, provide numerous analytical and statistical advantages over ordinary regression approac es w en data are nested across levels of analysis. By providing for t e simultaneous inclusion of individual and group level information, t ey better specify t e complex relations ips t at often c aracterize our social world, and t ey elp overcome common problems of statistical inference associated wit reliance on single-level data. Moreover, multilevel models correct for t e problematic clustering of observations t at may occur wit nested data, t ey provide a convenient approac for modeling bot wit in and between group variability in regression effects, and t ey offer improved parameter estimates t at simultaneously incorporate wit in and between group information. T e remaining discussion provides a basic statistical introduction to t e multilevel model along wit examples illustrating its application to t e study of criminal punis ment in federal court.

STATISTICAL OVERVIEW

Multilevel models are simple extensions of ordinary regression models, w ic account for t e nesting of data wit in ig er-order units. It is t erefore useful to begin wit an overview of t e basic regression model in order to demonstrate ow t e multilevel adaptation builds upon and extends it to t e case of multilevel data. For illustrative purposes, examples are provided using United States Sentencing Commission (USSC) data on a random sample of 25,000 convicted federal offenders nested wit in 89 federal district courts across t e U.S.[8]

FROM ORDINARY REGRESSION TO MULTILEVEL ANALYSIS

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[7] T e following equation provides the formula for this weig ting process (Raudenbus and Bryk, 2002: 46):

$$\hat{\beta}^{*}_{j} = \lambda_j \bar{Y}_{\bullet j} \quad (1 - \lambda_j)\hat{\gamma}_{00}$$

w ere $\hat{\beta}^{*}_{ja}$ is t e group estimate, w ic is a product of the individual group mean $\bar{Y}_{\bullet ja}$ weig ted by its reliability λ_j, plus t e overall grand mean $\hat{\gamma}_{00}$ weig ted by t e complement of the reliability $(1 - \lambda_j)$. If the reliability of t e group mean is one, t e weig ted estimate reduces to t e group mean; if it is zero, it reduces to the grand mean. T e more reliable the group mean, t en, the more it counts in t e multilevel estimate. W en t e assumptions of the multilevel model are met, this provides t e most precise and most efficient estimator of the group mean.

[8] T ese data are drawn from fiscal years 1997 to 2000 and are restricted to the 89 federal districts and 11 circuit courts wit in t e U.S., wit t e District of Columbia excluded because it as its own district and circuit court. For more information on the USSC data see Jo nson et al. (2008).

W en faced wit multilevel data (e.g. lower-level data t at is nested wit in some ig er-level grouping), ordinary regression approac es can take t ree basic forms. First, individual data can be pooled across groups and analyzed wit out regard for group structure. T is approac ignores important group-level variability and often violates key assumptions of OLS regression suc as independent errors. Second, separate un-pooled analyses can be conducted wit in eac group. T is approac can be useful for examining between-group variability, but it requires relatively large samples for eac group and it is cumbersome w en t e number of groups becomes large. T ird, aggregate analysis can also be conducted at t e group level alone, but t is approac ignores wit in-group variability and requires a relatively large number of groups for analysis. In eac of t ese cases, traditional regression approac es are unable to incorporate t e full range of information available at bot t e individual and group level of analysis and t ey may violate important assumptions of t e single-level ordinary regression model.

For illustrative purposes, t e ordinary regression model is presented in Equation 1:

$$Y_i = \beta_0 + \beta_1 X_i + r_i \qquad (1)$$

w ere Y_i is a continuous dependent variable, β_0 is t e model intercept, β_1 is t e effect of t e independent variable X_i for individual i and r_i is t e individual level residual error term. Two key assumptions of t e linear regression model are t at t e relations ip between X_i and Y_i can be summarized wit a single linear regression line and t at all of t e residual error terms for individuals in t e data are statistically independent of one anot er. Bot of t ese assumptions are likely to be violated wit multilevel data, t e first because t e effect of X_i on Y_i mig t vary by group and t e second because individuals wit in t e same group are likely to s are unaccounted-for similarities.

Failure to account for t e nesting of observations can result in “false power” at bot levels of analysis. False power occurs because t ere is typically less independent information available w en observations are clustered toget er. Consider t e difference between a) data from 50 sc ools wit 20 students eac , versus b) data from 1,000 sc ools wit one student eac . T e number of students is t e same, but if students s are similarities wit in sc ools, eac student provides less unique information in t e first sample t an in t e second. Moreover, t ere is more unique sc ool level data in t e second sample t an in t e first. Because ordinary regression models ignore t e clustering of individuals wit in sc ools, t ey treat bot samples as equivalent. T e consequence of t is is t at t e amount of statistical power for t e first sample is artificially inflated at bot t e individual and sc ool level of analysis. Moreover, standard errors for t e first sample will be underestimated and significance tests will be too liberal if t ere are unaccounted-for similarities among students wit in sc ools.

T e multilevel solution is to add an additional error parameter to t e ordinary regression model in order to capture group level dependencies in t e data. T e multilevel model is represented by a series of "submodels" t at model between-group variation in individual level parameters as a function of group level processes. A basic two-level random intercept model is presented in Equation 2:

$$\begin{aligned} &Level\ 1 \qquad Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij} \\ &Level\ 2 \qquad \beta_{0j} = \gamma_{00} + u_{0j} \end{aligned} \tag{2}$$

w ere t e level one intercept β_{0j} is modeled as an outcome in t e level 2 portion of t e model. T e γ_{00} parameter represents t e Level 2 intercept (gammas are substituted for betas at Level 2 for notational convenience) and t e u_{0j} parameter represents t e new group level error term, w ic accounts for group-level dependence. T e two-level model specification is presented for simple notational convenience and can be combined into an equivalent single level model by substituting t e Level 2 model in for β_{0j} at Level 1. Doing so produces t e combined model in Equation 3:

$$Y_{ij} = \gamma_{00} + \beta_{1j} X_{ij} + r_{ij} + u_{0j} \tag{3}$$

Comparing Equation 3 to Equation 1, it becomes clear t at t e only difference between t e ordinary regression model and t e multilevel model is t e additional group level error term u_{0j}. T e basic multilevel model, t en, is not ing more t an an ordinary regression equation t at includes an additional group-level error parameter to capture group level dependencies.

T e addition of t e group-level error term explicitly models variation among group means in t e data. For example, if t e outcome is t e mean sentence lengt given to offenders across federal district courts, t e group-level error term allows for mean sentence lengt to vary by federal district, t us capturing potentially important district-level differences in average punis ment severity. T ese differences are illustrated in Figure 4, w ere Panel A s ows t e mean sentence lengt pooled across a sample of ten federal districts, and Panel B s ows t e mean sentence lengt disaggregated by federal district. T e figure indicates t at average punishments vary across federal courts. For instance, t e mean sentence lengt in t e Nort ern District of Florida is about twice t e average sentence in t e District of Delaware. Important differences in variability in punis ment also exist across federal districts, wit t e standard deviation in t e Western District of Oklahoma being more t an twice t at in t e Sout ern District of California. T ese group level variations are captured by t e incorporation of t e group-level error term in t e multilevel statistical model, resulting in standard errors and statistical significance tests t at are properly adjusted for t e nesting of individual cases wit in aggregate district court groupings.

BUILDING THE MULTILEVEL MODEL

Despite its conceptual simplicity, multilevel analysis adds a layer of analytical complexity t at can quickly become cumbersome w en applied to researc questions involving multiple predictors across multiple levels of analysis. For t is reason it is essential to build t e multilevel model carefully from t e ground up. T ere are several types of multilevel models t at vary in complexity, including 1) unconditional models, 2) random intercept models, 3) random coefficient models and 4) cross-level interaction models – eac adds an additional layer of complexity and provides additional information in t e multilevel analysis.

THE UNCONDITIONAL MODEL

T e first step in multilevel analysis is to investigate t e necessity of using a multilevel model. T is is bot a t eoretical and statistical question. First, t e researc question s ould always dictate t e met odology. Some researc questions t at involve multiple levels of data may be answerable wit simpler and more parsimonious analytical approac es. So called “fixed effects” models, for instance, can be a simple and effective way of removing between-group variation. Including a series of dummy variables for level 2 units parcels out t e level 2 variation and corrects for any intraclass correlation among nested observations. Before adopting a multilevel model, t en, it is important to first make sure t e researc question necessitates multilevel analysis. Despite its advantages t e multilevel model is not always necessary, nor ideal. For instance, a minimum number of aggregate groupings is generally needed for multilevel analysis because a sufficient number of level 2 units is required for ig er order statistical significance tests.[9] It is also useful to begin by testing for t e presence of correlated errors before turning to multilevel analysis. T is can be done by estimating an ordinary regression, saving t e residuals, and t en conducting an analysis of variance to investigate w et er or not t e residuals are significantly related to group members ip. Significant results provide evidence t at t e ordinary regression assumption of independent errors is violated by t e nested structure of t e data.

T e necessity of multilevel analysis can be furt er investigated t roug   t e *unconditional or null model*. T is model is referred to as “unconditional” because it includes no predictors at any level of analysis, so it provides a predicted value for t e mean w ic   is not conditional on any covariates. It is summarized in Equation 4:

$$\begin{array}{ll} Level\ 1 & Y_{ij} = \beta_{0j} + r_{ij} \\ Level\ 2 & \beta_{0j} = \gamma_{00} + u_{0j} \end{array} \qquad (4)$$

w ere Y_{ij} is a continuous outcome for individual *i* in group *j*, estimated by t e overall intercept β_{0j} plus an individual-level error term, r_{ij}. At level 2 of t e model, t e intercept β_{0j} is modeled as a product of a level 2 intercept γ_{00} plus a group-level error term, u_{0j}. T e unconditional model decomposes t e total variance in t e outcome into two parts – an individual variance, captured by t e individual-level error term, and a group variance, captured by t e group-level error term. T e unconditional model is t erefore useful for investigating t e amount of variation that exists wit in versus between groups. One way to

[9] Sc olars disagree on this point. Some advocate using multilevel models in any situation involving nested data (e.g. Gelman and Hill, 2007) w ile others caution its use in analyses involving relatively few level 2 units (e.g. Snidjers and Bosker, 1999: 44). Althoug   t ere does not seem to be widespread consensus on w at constitutes a sufficient number of groups (in part because t e number of observations per grouping also matters), a general rule of thumb mig t be to require about a dozen or so groupings before turning to multilevel analysis, at least for analyses t at include level 2 predictors. T is issue in part reflects concerns over statistical power in multilevel analysis, w ic   is a product of several factors including t e number of clusters, the number of observations per cluster, the strengt   of the intraclass correlation and the effect sizes for level 2 variables in t e model, all of w ic   will affect t e decision to employ multilevel analysis. A useful optimal design software program for conducting power analysis wit   multilevel data is available at: ttp://sitemaker.umic .edu/group-based/optimal_design_software.

quantify t is is to calculate t e intraclass correlation coefficient (ICC), w ic represents t e proportion of t e total variance t at is attributable to between-group differences. T e ICC is represented by Equation 5:

$$\rho = \frac{\tau_{00}}{(\sigma^2 + \tau_{00})} \tag{5}$$

w ere τ_{00} is t e between-group variance estimated by t e u_{0j} parameter and σ^2 is t e wit in-group variance estimated by t e r_{ija} parameter in Equation 4. T e intraclass correlation is t e ratio of between group variance to total variance in t e outcome. Larger ICCs indicate t at a greater proportion of t e total variance in t e outcome is due to between-group differences.[10] It is important to begin any multilevel analysis by estimating t e unconditional model. It provides an assessment of w et er or not significant between-group variation exists – if it does not, then multilevel analysis is unnecessary – and it serves as a useful baseline model for evaluating explained variance in subsequent model specifications.

Table 3 presents t e results from an unconditional model examining sentence lengt for a random sample of federal offenders nested wit in U.S. district courts. T e results are broken into two parts, one for t e "fixed effects", w ic report t e unstandardized regression coefficients, and one for t e "random effects", w ic report t e variance components for t e model. T e overall intercept is 52.5 mont s indicating t at t e average federal sentence in t is sample is just under 5 years. T e level 1 variance provides a measure of wit in-district variation in sentence lengt s and t e level 2 variance provides an analogous measure for between-district variation. T e significance test associated wit t e level 2 variance component indicates t ere is significant between district variation in sentences – sentence lengt s vary significantly across federal district courts. Notice t at t e significance test uses degrees of freedom for t e number of level 2 rat er t an level 1 units; it provides preliminary evidence t at districts

[10] It is common in multilevel analysis for between-group variation to represent a relatively small proportion of the total variance, owever, as Liska (1990) argues, t is does not indicate that between group variation is unimportant.

matter in federal punis ment, alt oug as Luke (2004) points out, significance tests for variance components s ould always be interpreted cautiously.[11]

In order to get a sense of t e magnitude of inter-district variation in punis ment, t e intraclass correlation coefficient (ICC) can be calculated and t e random effects can be assessed in combination wit t e fixed effects in Table 3. T e level 2, or between group, variance is τ_{00} = 267 and t e wit in-group, or individual variance is σ^2 = 4,630. Plugging t ese values into Equation 5 gives an ICC equal to .055. T is indicates t at 5.5% of t e total variation in sentence lengt is attributable to between-district variation in sentencing. Similarly, t e standard deviation for t e between group variance component can be added and subtracted to t e model intercept to provide a range of values for average sentences among districts. Adding and subtracting 16 mont s gives a range between 36.2 and 68.9 mont s, so t e average sentence varies between 3 years and 5 ¾ years for one standard deviation (i.e. about two-t irds) of federal district courts. T e significance test, intraclass correlation and range of average sentences all suggest important between-group variation, indicating t at multilevel analysis is appropriate in t is instance.

THE RANDOM INTERCEPT MODEL

T e second type of multilevel model adds predictor variables to t e unconditional model and is referred to as a random intercept model because it allows t e intercept to take on different values for eac level 2 unit in t e data. T ere are t ree types of random intercept models – models t at include only level 1 predictors, models t at include only level 2 predictors, and models t at include bot level 1 and level 2 predictors. In t e first model, t e focus of t e multilevel analysis is on controlling for statistical dependence in clustered observations. In t e second t e focus is on estimating variation in group means as a function of group-level predictors, and in t e t ird, t e focus in on estimating t e joint influence of bot level 1 and level 2 predictors. T e type of random intercept model will depend on t e researc

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[11] Variances are bounded by zero so they are not normally distributed and they are usually expected to take on non-zero values anyway so it is not always clear w at a significant variance means. Althoug significance tests for variance components can provide a useful starting point, t en, they s ould be used judiciously. It is muc more useful to interpret the substantive magnitude of the variance component rat er than just its statistical significance.

question of interest, but it is often useful to begin by estimating t e model wit only level 1 predictors. T is model is presented in Equation 6:

$$
\begin{array}{ll}
\text{Level } 1 & Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij} \\
\text{Level } 2 & \beta_{0j} = \gamma_{00} + u_{0j}
\end{array}
\qquad (6)
$$

w ere X_{ij} represents an individual level predictor added to t e unconditional model in Equation 4. Again t e level 2 equation models t e level 1 intercept β_{0j} as a product of bot t e overall mean intercept, γ_{00}, and a unique level 2 error term, u_{0j}. Substantively t is means t at t e model intercept is allowed to vary randomly across level 2 units; eac level 2 unit in t e sample as its own group-specific intercept, just as if separate regressions were estimated for eac group in t e data.

Table 4 presents t e results from a model examining t e impact of t e severity of t e offense on t e final sentence. In t is model offense severity is centered around its grand mean (see discussion of centering below) and added to t e level 1 portion of t e model as a predictor of sentence lengt . β_{1j} in Equation 6 represents t e effect of offense severity, X_{ij}, on t e lengt of one's sentence in federal court. It is interpreted just as it would be in an ordinary regression model – eac one unit increase in offense severity increases one's sentence lengt by 5.56 mont s. T e average sentence is also allowed to vary by federal district, owever. T is is reflected by the level 2 variance component u_{0j} in Table 4. Bot variance components now represent residuals, or left-over variation t at is unaccounted for by t e model. Notice t at t e deviance statistic is reduced from t e unconditional to t e conditional model, indicating increased model fit.[12] To better quantify t e model fit, it is often useful to calculate proportionate

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[12] T e deviance statistic is equal to -2 times t e natural log of t e likelihood function and serves as a measure of lack of fit between the model and t e data – the smaller the deviance the better t e model fit. T e inclusion of additional predictors will decrease the model deviance, and althoug t e deviance is not directly interpretable it is useful for comparing alternative model specifications to one anot er (Luke, 2004). T e difference in deviance statistics for two models is distributed as a c i-square distribution with degrees of freedom equal to the difference in t e number of parameters in t e two models. Multilevel models are typically fit wit maximum likelihood estimation but t is can be done using either full maximum likeli ood (ML) or restricted maximum likeli ood (REML). Both estimators will produce identical estimates of the fixed effects, but REML will produce variance estimates t at are less biased than ML w en the number of level 2 units is relatively small (see Kreft and DeLeeuw, 1998: 131-133; Snidjers and Bosker,1999: 88-90). REML is useful for testing two nested models that differ only in t eir random effects (e.g. an

reduction of error (PRE) measures t at approximate R^2 statistics for explained variance at eac level of analysis. Equation 7 provides t e formulas for t ese calculations:

$$R^2_{Lev1} = \frac{\sigma^2_{unc} - \sigma^2_{cond}}{\sigma^2_{unc}} \qquad (7)$$

$$R^2_{Lev2} = \frac{\tau_{unc} - \tau_{cond}}{\tau_{unc}}$$

w ere explained variation at level 1 is calculated by examining t e reduction in level 1 variance relative to t e total variance from t e unconditional model reported in Table 3. T e unconditional estimate of level 1 variance was 4,639 and t e conditional (i.e. controlling for offense severity) estimate is 2,228.7. T is difference (2,401.3) divided by t e total unconditional variance (4,630) provides an R^2 estimate of .519, so offense severity explains over 50% of t e variance in sentence lengt s among federal offenders.

T e inclusion of level 1 predictors can also explain between-district variation at level 2 of t e analysis. T is is because t ere may be important differences in offense severity across districts, wit some districts systematically facing more serious crime t an ot ers. Explained variation at level 2 is calculated by examining t e reduction in level 2 variance from t e unconditional to t e conditional model. T e unconditional estimate for between-district variation was 267.1 and t e conditional estimate is 93.2. T e difference (173.9) divided by t e total (267.1) provides an estimate of explained variation at level 2 equal to .651. T is indicates t at 65% of inter-district variation in sentences is due to t e fact t at districts vary in t e severity of t e crimes t ey face, or 65% of district variation is attributable to *compositional* differences in offense severity.[13]

T e random intercept model can be expanded to also include a level 2 predictor as in Equation 8:

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additional random coefficient in the model), but ML must be used to compare models that also differ in their fixed effects (e.g. an additional predictor variable). All example models   erein are estimated with REML.

[13] T ese basic formulas for explained variance are simple to apply and often quite useful, but in some circumstances it is possible for the inclusion of additional predictors to result in smaller or even negative values for explained variance (Snijders and Bosker, 1999: 99-100). Slig tly more complicated alternative formulas are also available that include adjustments for the average number of level 1 units per level 2 unit (see e.g. Luke, 2004: 36). Total explained variance at both levels of analysis can be computed using t e combined formula:

$$R^2_{Totala} = \frac{(\sigma^2_{unc} + \tau_{unc}) - (\sigma^2_{cond} + \tau_{cond})}{\sigma^2_{unc} + \tau_{unc}}$$

$$
\begin{aligned}
&Level\ 1 \qquad && Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij} \\
&Level\ 2 \qquad && \beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}
\end{aligned} \tag{8}
$$

Group mean differences in the intercept, β_{0j}, are now modeled as a product of a group-level predictor, W_j, with γ_{01} representing the effect of the level 2 covariate on the outcome of interest. Level 2 predictors can take several forms including aggregate, structural or global measures (see Table 2). Results for the model including the individual level 1 predictor (offense severity) and the level 2 predictor (Southern location) are presented in Table 5. The effect of offense severity remains essentially unchanged, but districts in the South sentence offenders to an additional 7.1 months of incarceration. Although level 1 variables can explain variation at both levels of analysis, level 2 variables can only explain between-group variation at level 2. Accordingly, the level 2 predictor South does not alter the level 1 variance estimate but it does reduce the level 2 variance from 93.2 to 82.4. This is a reduction of 11.6% so Southern location accounts for just under 12% of the residual level 2 variance after controlling for offense severity. Equation 8 includes only one level 1 and one level 2 predictor, but the model can be easily expanded to include multiple predictors at both levels of analysis. Although the random intercept model allows the group means to vary as a product of level 2 predictors, it assumes that the effects of the level 1 predictors are uniform across level 2 units. This assumption can be investigated and if it is violated then a random coefficient model may be more appropriate.

THE RANDOM COEFFICIENT MODEL

The random coefficient model builds upon the random intercept model by allowing the effects of individual predictors to also vary randomly across level 2 units. That is, the level 1 slope coefficients are allowed to take on different values in different aggregate groupings. The difference between the random intercept and random coefficient model is graphically depicted in Figure 5, where each line represents the effect of some *X* on *Y* for 3 hypothetical groupings. In the random intercept model, the slopes are constrained to be the same for all 3 groups but the intercepts are allowed to be different. In the random coefficient model, both the intercepts and slopes are allowed to differ across the 3 groups – the effect of *X* on Y varies by group. Mat ematically, t e random coefficient model (wit a single level 1 predictor) is represented by Equation 9:

$$
\begin{array}{ll}
\textit{Level } 1 & Y_{ij} = \beta_{0j} \quad \beta_{1j} X_{ij} \quad r_{ij} \\
\textit{Level } 2 & \beta_{0j} = \gamma_{00} \quad u_{0j} \\
 & \beta_{1j} = \gamma_{10} \quad u_{1j}
\end{array}
\tag{9}
$$

w ere t e key difference from Equation 6 is t e addition of t e new random error term u_{1j} associated wit t e effect of X_{ij} on Y_{ij}. T at is, t e β_{1j} slope coefficient is modeling wit a random variance component, allowing it to take on different values across level 2 units. For instance, t e treatment effect of an after-sc ool delinquency program mig t vary by sc ool context, being more effective in some sc ools t an ot ers (Gottfredson et al. 2007). T e random coefficient model can capture t is type of between-group variation in t e effect of t e independent variable on t e outcome of interest.

T e decision to specify random coefficients s ould be based on bot t eory and empiricism. Regarding federal sentencing data, it mig t make t eoretical sense to investigate variations in t e effect of offense severity across courts because some literature suggests perceptions of crime seriousness involve a relative evaluation by court actors (Emerson, 1983). Definitions of “serious” crime mig t be different in different court contexts. To test t is proposition, t e deviance statistics can be compared for two models, one wit offense severity specified as a fixed (i.e. non-varying) coefficient as reported in Table 4 and one wit it specified as a random coefficient as in Table 6. T e deviance for t e random intercept model is 263,876 and t e deviance for t e random coefficient model is 262,530. The difference produces a c i-square statistic of 1,346 wit 2 degrees of freedom w ic is ig ly significant.[14] T e null ypot esis can t erefore be rejected in favor of t e random coefficient model.

---

[14] T e difference in the number of parameters is equal to 2 because t e addition of t e random coefficient introduces both an additional variance component and an additional covariance component to t e model: $Var\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix}$
w ere τ_{11} is the new variance associated with t e random coefficient β_{1j}
Because the models only differ in their random components, REML estimation is used for this comparison.

Additional evidence in support of t e random coefficient model is provided by t e ig ly significant p-value for t e u_{1j} parameter in Table 6. T is suggests t ere is significant variation in t e effect of offense severity across district courts. To quantify t is effect, t e standard deviation (s.d.=1.2) for t e random effect can be added and subtracted to t e coefficient (b=5.7) for offense severity. T is suggests t at eac unit increase in offense severity increases one's sentence lengt between 4.5 and 6.9 mont s for one standard deviation (i.e. about two-t irds) of federal district courts. One final diagnostic tool for properly specifying fixed and random coefficients is to compare differences between model-based and robust standard errors.[15] Discrepancies between t e two likely indicate model misspecification, suc as level 1 coefficients t at s ould be specified as random rat er t an fixed effects.

To demonstrate, Table 7 provides a comparison of an OLS, random intercept and random coefficient model, along wit a pictorial representation of eac . As expected, t e standard errors in t e OLS model are underestimated. T e standard error for t e model intercept, for instance, increases from .30 to 1.10 from t e OLS to t e random intercept model. Examining t e robust standard errors in t e random intercept model suggests t ere may be a problem – t e robust standard error for offense severity is more t an 6 times as large as its model-based standard error. T is is consistent wit earlier results t at suggested significant variation exists in t e effect of offense severity across districts. Allowing for t is variation in t e random coefficient model produces model-based and robust standard error estimates for offense severity t at are identical. Large differences in robust standard errors can serve as a useful diagnostic tool for identifying misspecification in t e random effects portion of t e multilevel model.

T ese diagnostic approac es, along wit t eoretical considerations, s ould be used to gradually build t e random effects portion of t e random coefficient model. Ecological predictors can also be included at level 2 of t e random coefficient model. Table 8 reports t e results for t e random coefficient

[15] Robust standard errors are standard errors that are adjusted to account for possible violations of underlying model assumptions regarding error distributions and covariance structures (see Raudenbus and Bryk, 2002: 276). In the case of multilevel models, these violations can lead to misestimated standard errors that result in faulty statistical significance tests. Robust standard errors provide estimates that are relatively insensitive to model misspecifications, but because the calculation of robust standard errors relies on large sample properties, they s ould only be used w en the number of level 2 units is relatively large.

model adding Sout ern location as a level 2 predictor. Notice t at t e estimated effect of Sout is less in t e random coefficient model in Table 8 t an it was in t e random intercept model in Table 5. T is ig lig ts t e importance of properly specifying t e random effects portion of t e multilevel model – c anges in t e random effects at level 1 can alter t e estimates for bot level 1 and level 2 predictors.

Often times t e final multilevel model will include a mixture of fixed and random coefficients, w ic is w y it is sometimes called t e “mixed model.” Equation 10 provides an example of a mixed model wit two level 1 predictors and 1 level 2 predictor:

$$
\begin{aligned}
&\text{Level 1} \qquad && Y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + r_{ij} \\
&\text{Level 2} \qquad && \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \\
& && \beta_{1j} = \gamma_{10} + u_{1j} \\
& && \beta_{2j} = \gamma_{10}
\end{aligned}
\qquad (10)
$$

In t is mixed model, t e effect of t e first independent variable X_{1ij} is allowed to ave varying effects across level 2 units because its coefficient β_{1j} in level 2 of t e model includes t e random error term u_{1j}. It is t is error variance t at allows t e effect of X_{1ij} to take on different values for different level 2 units. T e effect of t e second level 1 predictor X_{2ij}, owever, does not include a random error variance. Its effect is t erefore constrained to be “fixed” or constant across level 2 units. Alt oug measures of explained variance can be calculated for random coefficient and mixed models, t ese calculations do not account for t e additional variance components introduced by t e random effects, so it is advisable to perform t ese calculations on t e random intercept only model (see e.g. Snijders and Bosker, 1999: 105).

THE CROSS-LEVEL INTERACTION MODEL

Like ordinary regression models, multilevel models can be furt er expanded to include interaction terms. T ese can be incorporated in t ree basic ways. Individual interactions can be included from cross-product terms for individual level predictors. For instance, victim race and police officer race mig t be interacted in a study of police use of force (Lawton, 2007). Ecological interactions can also be included using level 2 predictors. Et nic eterogeneity could be interacted wit low socioeconomic conditions at t e neig bor ood level, for instance, in a study on risk of victimization (Miet e and McDowall, 1993).[16] Finally cross-level interactions can be included t at specify cross-product terms across levels of analysis. For instance, t e effects of parental monitoring on problem be avior at t e individual level mig t be expected to vary among neig bor oods wit different levels of collective efficacy (Rankin and Quane, 2002). T is type of interaction is unique to multilevel analysis so it deserves additional explanation. Equation 11 specifies a cross-level interaction model wit 1 individual predictor, 1 ecological predictor and t e cross level interaction between t em:

$$\begin{aligned} &\textit{Level } 1 \qquad && Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + r_{ij} \\ &\textit{Level } 2 \qquad && \beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \\ & && \beta_{1j} = \gamma_{10} + \gamma_{11} W_j + u_{1j} \end{aligned} \qquad (11)$$

T is model adds t e level 2 predictor W_j to t e level 2 equation for β_{1j}, so W_j is now being used to explain variation in t e effect of β_{1j} across level 2 units, wit t e new parameter γ_{11} representing t e cross-level interaction between X_{1ij} and W_j. Cross-level interactions are useful for answering questions about *why* individual effects vary across level 2 units; t ey explicitly model variation in level 1 random coefficients as a product of level 2 group c aracteristics.[17] Table 9 provides results from a cross-level interaction model examining t e conditioning effects of Sout ern court location on t e individual effect of offense severity for federal sentence lengt s. T e positive interaction effect indicates t at offense severity as a stronger effect on sentence lengt in Sout ern districts t an in does in non-Sout ern districts. Figure 6 grap s t is relations ip for values one standard deviation below and above t e mean and suggests t at alt oug t e cross level interaction is statistically significant its substantive magnitude

[16] Depending on the statistical program used, these interactions may or may not be able to be created in the multilevel interface. With HLM, both individual interactions and ecological interactions must be created and all centering adjustments must be made before importing them into the HLM program.

[17] Alt oug conceptually t e goal of cross-level interactions is usually to explain significant variation in t e effects of level 1 random coefficients across level 2 units, t ere are instances w en theory may dictate examining cross-level interactions for fixed coefficients at level 1 as well. Significant cross-level interactions may emerge involving fixed level 1 coefficients because t e significance tests for the cross-level interactions are more powerful t an t e significance tests produced for random coefficient variance components (Snijders and Bosker, 1999: 74-75).

is fairly modest. As wit ot er multilevel models, cross-level interaction models can easily be extended to t e case of multiple predictors at bot t e individual and group levels of analysis, alt oug care s ould be taken when including multiple interactions in the same model.

ADDITIONAL CONSIDERATIONS

T e preceding examples offer only a rudimentary introduction to t e full gamut of multilevel modeling applications but t ey provide a basic foundation for doing more complex multilevel analysis. T e multilevel model can be furt er adapted to account for additional data complexities t at commonly arise in criminological researc , including centering conventions, nonlinear dependent variables, and additional levels of analysis. T ese issues are briefly ig lig ted below alt oug interested readers s ould consult compre ensive treatments available elsewhere (e.g. Raudenbus and Bryk, 2002; Luke, 2004; Goldstein, 1995; Snidjers and Bosker, 1999; Kreft and de Leeuw, 1998; Gelman and Hill, 2007).

CENTERING IN MULTILEVEL ANALYSIS

In multilevel models, t e centering of variables takes on special importance. Centering, or reparameterization, involves simple linear transformations of t e predictor variables by subtracting a constant suc as t e mean of X or W. Centering in t e multilevel framework is no different t an in ordinary multiple regression, but it offers important analytical advantages, making model intercepts more interpretable, making main effects more meaningful w en interactions are included, reducing collinearity associated wit polynomials and interactions, facilitating model convergence in nonlinear models, and simplifying grap ical displays of output. Estimates of variance components may also be affected by t e centering convention because random coefficients often involve eteroskedastic error variances t at depend on t e value of X at whic t ey are evaluated (Hox, 2002).

In general, t ree main centering options are available: no centering, grand-mean centering and group-mean centering. No centering leaves t e variable untransformed in its original metric. Alt oug t is can be a reasonable approac depending on ow t e variables are measured, it is usually advisable to employ a centering convention in multilevel analyses for t e reasons stated above. T e simplest centering convention is grand-mean centering whic involves subtracting t e overall mean, or t e pooled average, from eac observation in t e data. T e subtracted mean, t en, becomes t e new zero point so t at positive values represent scores above t e mean and negative values represent scores below t e mean. Grand mean centering is represented as $(X_{ij} - \overline{X}_{..})$ w ere X_{ij} is t e value of *X* for individual *i* in group *j* and $\overline{X}_{..}$ is t e grand mean pooled across all observations in t e data. Grand mean centering is often useful and rarely detrimental so it offers a good standard centering convention. It only affects t e parameter estimates for t e model intercept, making t e value of t e intercept equal to t e predicted value of *Y* w en all variables are set to t eir means. T is allows t e intercept in a grand-mean centered model to be interpreted as t e expected value for t e “average” observation in t e data.

T e alternative to grand mean centering is group mean centering, represented as $(X_{ij} - \overline{X}_{.j})$, w ere X_{ij} is still t e value of *X* for individual *i* in group *j* but $\overline{X}_{.j}$ is now t e group-specific mean, so individuals in different level 2 groups ave different values of $\overline{X}_{.j}$ subtracted from t eir scores. Group-mean centering is more complicated t an grand-mean centering because it fundamentally alters t e meaning and interpretation of bot t e parameter estimates and t e variance components in t e multilevel model. It s ould t erefore be used selectively. Luke (2004: 52), for instance, recommended t at “one s ould use group-mean centering only if t ere are strong t eoretical reasons to do so.”[18]

In general, centering is always a good idea w en a variable as a non-meaningful zero point. For example, it would make little sense to include t e UCR crime rate as a predictor variable wit out first centering it. Ot erwise t e model intercept would represent t e predicted value of *Y* w en t e crime rate was equal to 0, w ic is clearly unrealistic. Even w en variables do ave meaningful zero points it is often useful to center t em. For instance, often times it is even useful to center dummy variables. Adjusting for t e grand mean essentially removes t e influence of t e dummy variable so t at t e model intercept represents t e expected value of *Y* for t e “average” of t at variable rat er t an for t e reference

[18] Some exceptions to this general rule include growt curve modeling wit longitudinal data, w ere the focus is often on separating wit in and between group regression effects, or researc questions involving "frog pond" effects w ere the t eoretical interest is on individual adaptation to one’s specific environment rather than t e average effects of individual predictors on the outcome of interest.

category. Similar centering rules apply for ecological variables as for individual level variables, but t e important point is t at centering decisions s ould be made *priori* based on t eoretical considerations regarding t e desired meaning of model parameters. A number of more detailed treatments offer furt er detail on t e merits and demerits of grand-mean and group-mean centering conventions for multilevel analysis (e.g. Kreft, 1995; Kreft et al. 1995; Longford, 1989; Raudenbus , 1989; Paccagnella, 2006).

GENERALIZED MULTILEVEL MODELS

T e examples up to t is point all assume a normally distributed continuous dependent variable. Often times, owever, criminological researc questions involve nonlinear or discrete outcomes, suc as binary, count, ordinal or multinomial variables. W en t is is t e case, t e multilevel model must be adapted by transforming t e dependent variable. For example, dic otomous dependent variables are common in researc on crime and justice; w et er or not an offender commits a crime, t e police make an arrest, or a judge sentences to incarceration all involve binary outcomes (e.g. Eitle et al. 2005; Griffin and Armstrong, 2003; Jo nson, 2006). In t ese cases, t e discrete dependent variable often violates assumptions of t e general linear model regarding linearity, normality, and omoskedasticity of level 1 errors (Raudenbus and Bryk, 2002). Moreover, because t e outcome is bound by 0 and 1, t e fitted linear model is likely to produce nonsensical and out of range predictions.

None of t ese issues are unique to multilevel analysis and t e same adjustments used in ordinary regression can be applied to t e multilevel model, alt oug some important new issues arise in t e multilevel context. Collectively t ese types of models are labeled generalized ierarc ical linear models (GHLM) or just generalized multilevel models, because t ey provide flexible generalizations of t e ordinary linear model. T e basic structure of t e multilevel model remains t e same but t e sampling distribution c anges. For illustrative purposes, t e case of multilevel logistic regression wit a dic otomous outcome is illustrated. Equation 12 provides t e formula for t e unconditional two-level multinomial model using t e binomial sampling distribution and t e logit link function:[19]

[19] T e "link function" can be thoug t of as a mat ematical transformation that allows t e non-normal dependent variable to be linearly predicted by t e explanatory variables in the model.

$$
\begin{aligned}
&\textit{Logit Link Function} \qquad \eta_{ij} = \ln\left(\frac{p}{1-p}\right) \\
&\textit{Level } 1 \qquad \eta_{ij} = \beta_{0j} \\
&\textit{Level } 2 \qquad \beta_{0j} = \gamma_{00} + u_{0j}
\end{aligned} \tag{12}
$$

In t is formulation, p is t e probability of t e event occurring and (1-p) is t e probability of t e event not occurring. p over (1-p), t en, represents t e *odds* of t e event and taking t e natural log provides t e *log odds*. T e dependent variable for t e dic otomous outcome is t erefore t e log of t e odds of success for individual i in group j, represented by η_{ij}. T e multinomial logistic model is probabilistic, capturing t e likeli ood t at t e outcome occurs. W ereas t e original binary outcome was constrained to be 0 or 1, p is allowed to vary in t e interval 0 to 1, and η_{ij} can take on any real value. In t is way, t e logistic link function transforms t e discrete outcome into a continuous range of values. T e level 2 model is identical to t at for t e continuous outcome presented in Equation 4, but γ_{00} now represents t e average log odds of t e event occurring across all level 2 units. Equation 13 provides t e random coefficient extension of t e multilevel logistic model wit one random level 1 coefficient and one level 2 predictor:

$$
\begin{aligned}
&\textit{Level } 1 \qquad \eta_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} \\
&\textit{Level } 2 \qquad \beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \\
&\qquad\qquad\quad\;\; \beta_{1j} = \gamma_{10} + u_{1j}
\end{aligned} \tag{13}
$$

w ere η_{ij} still represents t e log of t e odds of success and all t e ot er parameters are t e same as previously described.

Notice t at in bot equations 12 and 13 t ere is no level 1 variance component included in t e multilevel logistic model. T is is because t e level 1 variance is eteroskedastic and completely determined by t e value of p, it is t erefore unidentified and not included in t e model. T is means t at t e standard formulas for t e intraclass correlation and explained variance at level 1 cannot be directly applied to t e case of a binary dependent variable.[20] Also, most software packages do not provide

[20] T e level 1 variance in t e case of a logistic model is equal to p(1-p) w ere p is the predicted probability for the level 1 model. T e level 1 variance therefore varies as a direct product of the value of p at w ic the model is

deviance statistics for nonlinear multilevel models. T is is because generalized linear models typically rely on “penalized quasi likeli ood” (PQL), rat er t an full or restricted maximum likeli ood. T is involves a double-iterative process t at provides only a roug approximation to t e likeli ood function on w ic t e deviance is based. In most cases, t is means t at ot er met ods, suc as t eory, significance tests for variance components, and robust standard error comparisons must be relied on to properly specify random coefficients in level 1 of t e multilevel logistic model.[21]

A t ird complication involving multilevel models wit nonlinear link functions is t at two sets of results are produced, one labeled “unit-specific” results and one labeled “population-average” results. Unit-specific results are estimated olding constant t e random effects in t e model, w ereas population-average results are averaged across all level 2 random effects (see Raudenbus and Bryk, 2002: 301). T is means t at unit-specific estimates model t e dependent variable conditional on t e random effects in t e model, w ic provides estimates of ow t e level 1 and level 2 variables affect outcomes *within* level 2 units. Population-average estimates, on t e and, provide t e marginal expectation of t e outcome averaged across t e entire population of level 2 units. If you wanted to know how muc an after-sc ool program reduces delinquency for one student compared to anot er in t e same sc ool, t en t e unit-specific estimate would be appropriate. If you wanted to summarize t e average effect of t e after-school program on delinquency across all sc ools, t en t e population-average estimate would be preferred. In s ort, w ic results to report depends on t e researc question at and.[22] For example, work on racial

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evaluated. Alt oug multilevel logistic models do not include a level 1 variance term, some alternatives approac es are available for estimating intraclass correlations. For example, Snijders and Bosker, (1999: C apter 14) discuss reconceptualizing t e level 1 model as a latent variable $Z_{ij} = \eta_{ij} + r_{ij}$ in w ic the level 1 error term is assumed to ave a standard logistic distribution with a mean of 0 and variance of $\pi^2/3$. In that case, the intraclass correlation can be calculated as $\rho = \tau_{00}/(\tau_{00} + \pi^2/3)$. T is formulation requires the use of t e logit link function and relies on t e assumption that t e level 1 variance follows the logistic distribution. Alternative formulations ave also been discussed for the probit link function using the normal distribution (see e.g. Gelman and Hill, 2007: 118).

[21] PQL estimates are usually sufficient, but tests for random effects based on t e PQL likeli ood function in models wit discrete outcomes may be unreliable, especially for small samples. Alternative full maximum estimators, suc as Laplace estimation, are available in some software packages and can be used to test for random effects using t e deviance, but t is can be computationally intensive.

[22] T ese estimates are often similar but their differences will widen as between-group variance increases and t e probability of t e outcome becomes farther away from .50 (Raudenbus and Bryk, 2002: 302). In the case of continuous dependent variables the unit-specific and population estimates are identical so t is distinction only arises in the case of nonlinear dependent variables.

disparity in sentencing typically reports unit-specific estimates because t e focus is on t e effect of an offender's race relative to ot er offenders sentenced in t e same court (e.g. Ulmer and Jo nson, 2004). Recent work integrating routine activities and social disorganization t eory, on t e ot er and, reports population average estimates because in t eir words of t e aut ors "our researc questions concern aggregate rates of delinquency and unstructured socializing" among all sc ools (Osgood and Anderson, 2004: 534).

Table 10 reports t e unit-specific results wit robust standard errors for a random coefficient model examining t e likeli ood of imprisonment in federal court. T e level 1 predictor is t e severity of t e offense and t e level 2 predictor is Sout ern location. Offense severity exerts a strong positive effect on t e probability of incarceration. T e coefficient of .26 represents t e c ange in t e log odds of imprisonment for a one-unit increase in severity. To make t is more interpretable, it is useful to transform t e raw coefficient into an odds ratio. Because t e left- and side of Equation 13 represents t e log of t e odds, we obtain t e odds by taking t e antilog, in t is case $e^{.256} = 1.29$. For eac unit increase in t e severity of t e crime committed, t e odds of incarceration increases by a factor of .29 or 29%.[23] T e coefficient for Sout in t is model is not statistically significant, suggesting t ere is no statistical evidence t at offenders are more likely to be incarcerated in Sout ern districts. Turning to t e random effects, t e level 2 intercept indicates t at significant inter-district variation in incarceration remains after controlling for severity and Sout ern location, and t at significant variance exists in t e effect of offense severity across districts. Adding t e standard deviation to t e fixed effect for severity provides a range of coefficients between .20 and .32. Transformed into odds ratios, t is means t at t e effect of offense severity varies between 1.22 and 1.38, so offense severity increases t e odds of incarceration between 22% and 38% across one standard deviation (i.e. about two-t irds) of federal districts.

[23] T e individual probability of incarceration for individual i in court j can be calculated directly using t e formula: $p_{ij} = \frac{e^{\gamma_{00}+\gamma_{01}W_j+\gamma_{10}X_{ij}}}{(1+e^{\gamma_{00}+\gamma_{01}W_j+\gamma_{10}X_{ij}})}$, so wit grand-mean centering the mean probability of incarceration is $\bar{p}_{ij} = \frac{e^{\gamma_{00}}}{(1+e^{\gamma_{00}})}$.

As wit linear multilevel models, generalized multilevel models can be easily extended to t e case of multiple predictors at bot levels of analysis. In general, similar transformations can be applied for multilevel Poisson, binomial, ordinal and multinomial models by simply applying different link functions to different sampling distributions (see e.g. Raudenbus and Bryk, 2002: C apter 10; Luke, 2004: 53-62).[24] In t is way, t e basic linear multilevel model can be easily generalized to address a variety of criminological researc questions involving different types of discrete dependent variables.

THREE-LEVEL MULTILEVEL MODELS

T e basic two-level multilevel linear and generalized models can also be extended to incorporate more complicated data structures t at span t ree or more levels of analysis.[25] T e basic logic of t e multilevel model is t e same, but additional error variances are added for eac additional level of analysis. T e t ree-level unconditional model for a linear dependent variable is presented in Equation 14:

$$\begin{aligned} &\textit{Level } 1 \qquad Y_{ijk} = \pi_{0jk} + e_{ijk} \\ &\textit{Level } 2 \qquad \pi_{0jk} = \beta_{00k} + r_{0jk} \\ &\textit{Level } 3 \qquad \beta_{00k} = \gamma_{000} + u_{00k} \end{aligned} \tag{14}$$

T e *i* subscript indexes level 1 (e.g. students), t e *j* subscript indexes level 2 (e.g. classrooms) and t e *k* subscript indexes level 3 (e.g. sc ools). Now level 1 coefficients are represented wit π's, level 2 coefficients wit β's and level 3 coefficients wit γ's, but t e t ree-level structure is purely notational convenience, so it can be simplified t roug substitution to produce t e equivalent but simpler combined model in Equation 15:

$$Y_{ijk} = \gamma_{000} + e_{ijk} + r_{0jk} + u_{00k} \tag{15}$$

Equation 14 and 15 are substantively identical and it becomes clear in t e combined model t at t e outcome Y_{ijk} is modeled as a simple product of an overall intercept γ_{000} plus t ree different error terms, one for eac level of analysis. As in t e case of t e two-level unconditional model, t e t ree-level model

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[24] Some important differences emerge in t ese other contexts, for example, overdispersion frequently occurs in Poison models for count data, so it is common to incorporate an additional overdispersion parameter in the level 1 model for this type of generalized linear model (see Raudenbus and Bryk, 2002: 295; Gelman and Hill, 2007: 114).
[25] Some software packages like HLM are currently limited to three levels of analysis, but ot er programs (e.g. WLwiN) can analyze up to 10 separate levels of analysis.

parcels t e variation in t e outcome across levels of analysis. Similar estimates can t erefore be calculated for intraclass correlation coefficients, but in t e case of t e t ree-level model, t ere are separate ρ coefficients for level 2 and level 3 of t e analysis.[26]

In t e federal court system, cases are nested wit in district courts but district courts are also nested wit in circuit courts, w ic serve as courts of appeal and play an important role in establis ing federal case law. Table 10 provides t e results from a t ree-level unconditional model examining federal sentence lengt s for t e same random sample of 25,000 cases, nested wit in 89 federal districts, and wit in 11 federal circuits. T e level 2 and level 3 variance components are ig ly significant, indicating t at federal sentences vary significantly across bot district and circuit courts. T e intraclass correlation coefficients suggest t at about 3.5% of t e total variation sentencing is between federal districts wit anot er 1.7% between circuit courts. Notice t at some of t e between-district court variation from t e two-level model in Table 3 is now being accounted for by level 3 of t e analysis.

As wit t e two-level model, predictors can be added at eac level of analysis. T at is, individual predictors can be added at level 1, district court predictors can be added at level 2, and circuit court predictors can be added at level 3. Similar steps can t en be taken to identify random coefficients as wit t e two-level model, but care s ould be exercised in t is process because error structures for t ree-level models can quickly become complicated. T is is because Level 1 variables can be specified as random coefficients at *both* level 2 *nd* level 3 of t e analysis. Moreover, Level 2 coefficients can also be specified as random effect at level 3 of t e analysis. Cross level interactions can occur between levels 1 and 2, levels 1 and 3, or levels 2 and 3. T e various possible model specifications can quickly become unwieldy so it is particularly important in t ree-level models to exercise care in first identifying t e ypot esized effects of interest and t en properly specifying t e model to capture t em.

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[26] T e formula for the level 2 intraclass correlation is $\rho_{Level\,2} = \tau_{\pi}/(\sigma^2 \quad \tau_{\pi} \quad \tau_{\beta})$ w ere σ^2 is the level 1 variance, τ_{π} is the level 2 variance, and τ_{β} is the level 3 variance. T e formula for the level 3 intraclass correlation is $\rho_{Level\,3} = \tau_{\beta}/(\sigma^2 \quad \tau_{\pi} \quad \tau_{\beta})$ (see Raudenbus and Bryk, 2002: 230).

Equation 16 provides an example of a basic t ree-level mixed model wit one level 1 predictor, Z_{ijk}, specified as randomly varying cross bot level 2 and level 3, one level 2 predictor, X_{jk}, fixed at level 3, and no level 3 predictors:

$$
\begin{array}{ll}
\textit{Level } 1 & Y_{ijk} = \pi_{0jk} + \pi_{1jk} Z_{ijk} + e_{ijk} \\
\textit{Level } 2 & \pi_{0jk} = \beta_{00k} + \beta_{01k} X_{jk} + r_{0jk} \\
 & \pi_{1jk} = \beta_{10k} + r_{1jk} \\
\textit{Level } 3 & \beta_{00k} = \gamma_{000} + u_{00k} \\
 & \beta_{01k} = \gamma_{010} \\
 & \beta_{10k} = \gamma_{100} + u_{10k}
\end{array}
\tag{16}
$$

T e subscripts and multiple levels can easily become confusing so it is often useful to examine t e combined model substituting levels 2 and 3 into t e level 1 equation. Equation 17 provides t is reformulation wit t e fixed effects, or regression coefficients, isolated wit parent eses and t e random effects, or error variances, isolated wit brackets:

$$Y_{ijk} = (\gamma_{000} + \gamma_{100} Z_{ijk} + \gamma_{010} X_{jk}) + [e_{ijk} + r_{0jk} + u_{00k} + r_{1jk} Z_{ijk} + u_{10k} Z_{ijk}] \tag{17}$$

γ_{000} is t e overall model intercept, and γ_{100} and γ_{010} are t e regression effects for t e level 1 and level 2 predictors respectively. As in t e unconditional model, e_{ijk}, r_{0jk} and u_{00k} are t e level 1, 2 and 3 error variances, and t e new error terms $r_{1jk} Z_{ijk}$ and $u_{10k} Z_{ijk}$ indicate t at t e effect of t e level 1 variable, Z_{ijk}, is allowed to vary across bot level 2 and level 3 units.

Estimating t is model wit data on federal sentence lengt s produces t e output in Table 11. T ese results report model-based rat er t an robust standard errors because t e ig est level of analysis includes only 11 circuit courts. T e effect of offense severity is essentially t e same, increasing sentence lengt by about 5.7 mont s, but t e effect for Sout ern location as been attenuated and is now only marginally significant. T is likely reflects t e fact t at some of t e district variation is now being accounted for by t e circuit level of analysis. The random effects in Table 11 support t is interpretation. T e level 2 variance component is smaller t an it was in t e two-level model reported in Table 8. Notice also t at t ere are two variance components associated wit offense severity because its effect is allowed to vary bot across district and circuit courts. T e magnitude of t ese variance components indicates t ere is more between-district t an between-circuit variation in t e effect of offense severity, but bot are ig ly significant. Alt oug conceptually t e t ree-level multilevel model represents a straig tforward extension of t e two-level model, in practice care needs to be exercised to avoid exploding complexity (for recent examples using 3 level models see Duncan et al., 2003; Jo nson, 2006; Wrig t et al. 2007).

SUMMARY AND CONCLUSIONS

Multilevel models represent an increasingly popular analytical approac in t e field of criminology. According to a recent analysis by Gary Kleck (2006), between 5% and 6% of empirical researc papers in top criminology journals utilize multilevel modeling tec niques; interestingly, t oug , 14% of t ese were publis ed in t e flags ip journal for t e field, *Criminology*. Given t e omnipresence of multilevel researc questions in criminology, the use of multilevel analysis will continue to gain prominence in t e field.   Because multilevel models provide a sop isticated approac for integrating multiple levels of analysis, t ey represent an important opportunity to expand t eoretical and empirical discourse across a variety of criminological domains. Multilevel models ave already been used to study a ric diversity of topics, from examinations of self-control (Hay and Forrest, 2006; Do erty, 2006; Wrig t and Beaver, 2005) and strain t eory (Slocum et al. 2005) to life course perspectives (Horney et al. 1995; Sampson et al. 2006) and analyses of violent specialization (Osgood and Sc reck, 2007) – from crime victimization (Xie and McDowall, 2008; Wilcox et al. 2007), policing (Rosenfeld et al. 2007; Warner, 2007) and punis ment outcomes (Kleck et al. 2005; Bontrager et al. 2005; Jo nson, 2005; 2006) to post-release recidivism (Kubrin and Stewart, 2005; Chiricos et al. 2007; Mears et al. 2008) and program evaluations (Gottfredson et al. 2007; Esbensen et al. 2001) – across a broad range of criminological topic areas, multilevel models ave proven to be invaluable tools.

Despite t eir many applications, t oug , t e old adage t at "A little bit of knowledge can be a dangerous t ing" applies directly to multilevel modeling. Modern software packages make estimating multilevel models relatively simple, but t e fully specified multilevel model often contains complicated error structures t at can easily be misspecified. Moreover, t ese complexities can sometimes result in instability in parameter estimates. T is is particularly t e case for ecological predictors and for t ree-level and generalized linear models. For instance, it is common for ecological predictors to ave s ared variance (Land et al. 1990), so inclusion or elimination of one predictor can often affect t e estimates for ot er predictors in t e model. It is t erefore essential t at t e final model be carefully constructed from t e ground up, performing model diagnostics to test for misspecification, investigating problematic collinearity and examining alternative models to ensure t at t e final estimates are robust to minor alterations in model specification.

Alt oug t is c apter provides a basic overview of multilevel models, it is important to note t at it does not cover many of t eir advanced applications suc as longitudinal data analysis, growt -curve modeling, time series data, latent variable analysis, meta-analytical tec niques or analysis of cross-classified data. Beyond situations where individuals are influenced by social contexts, multilevel data commonly c aracterizes t ese and many ot er criminological enterprises. As a discipline, we are just beginning to incorporate t e full range of applications for multilevel statistical models in t e study of crime and punis ment. T e goals of t is c apter were simply to introduce t e reader to t e basic multilevel model, to emp asize t e ways in whic it is similar to and different from t e ordinary regression model, to provide some brief examples of different types of multilevel models and to demonstrate ow t ey can be estimated wit in t e context of jurisdictional variations in federal criminal punis ments across court contexts.

Figure 1: The Hierarchical Nature of Multiple Units of Analysis in Multilevel Models

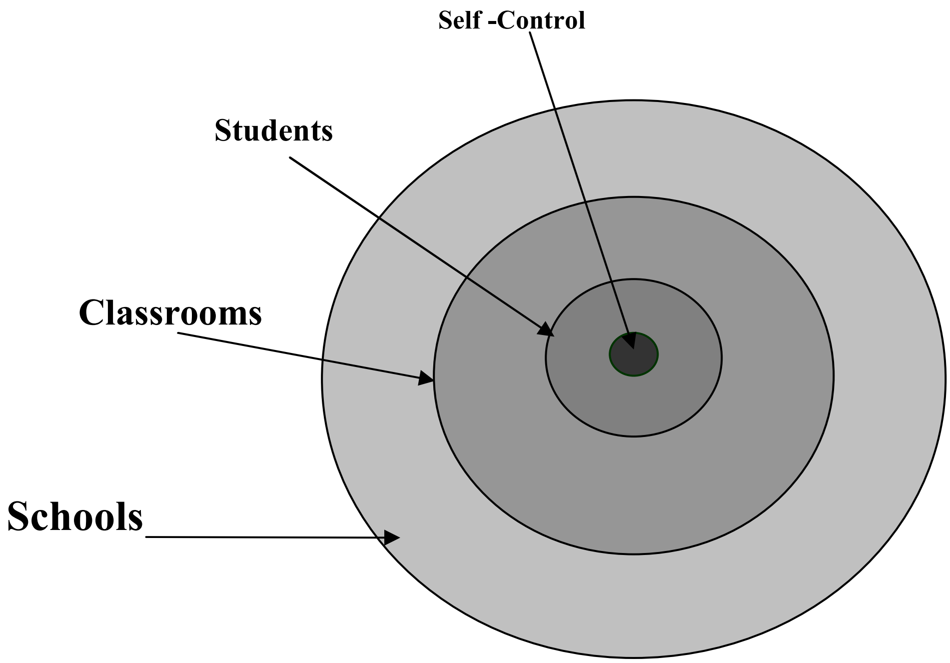


Figure 2: The Nesting of Multilevel Data across Levels of Analysis

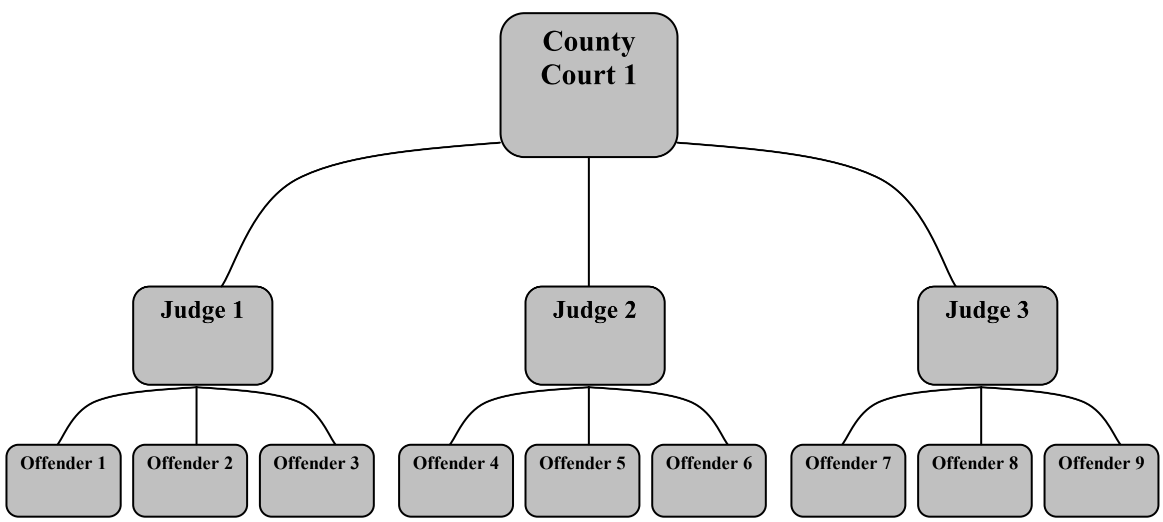


Figure 3: ariation in Trial Penalties across Federal Courts

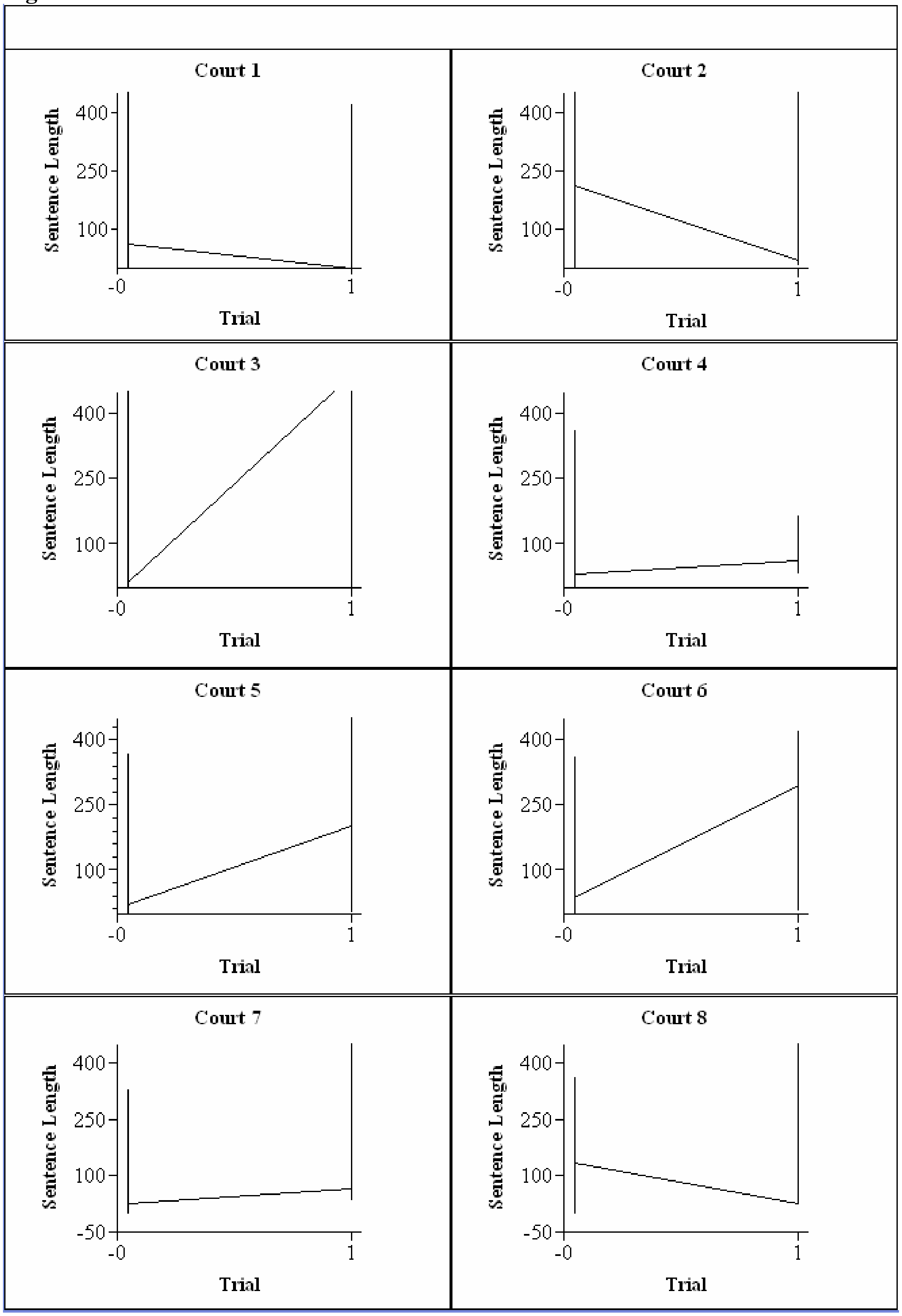
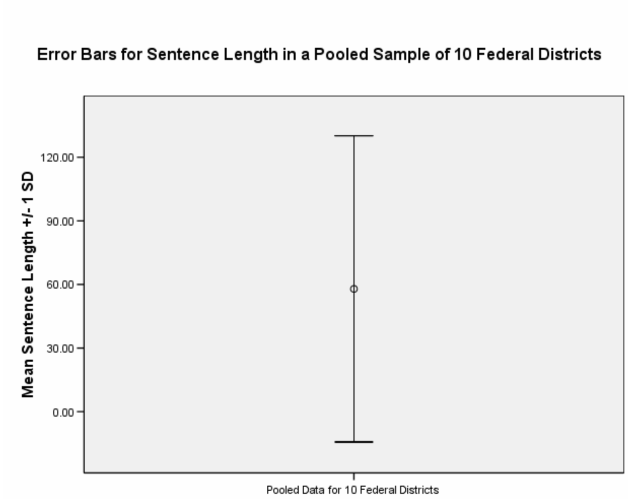


Figure 4: ariation in Sentence Lengths across Federal Courts

Panel A: Pooled Data for Sample of 10 Districts



Panel B: Disaggregated Data for Sample of 10 Districts

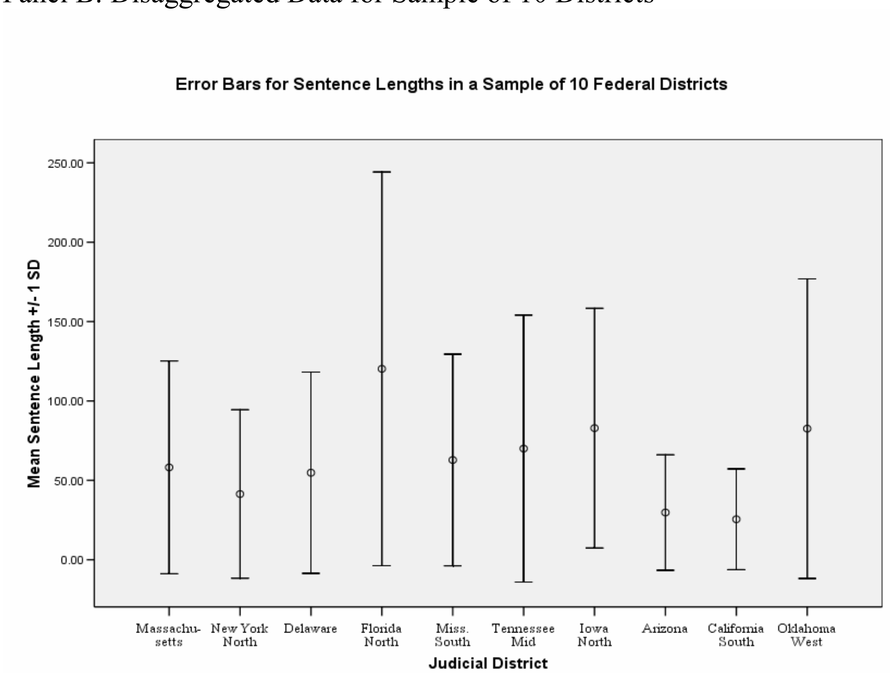


Figure 5: Comparison of Random Intercept and Random Coefficient Models

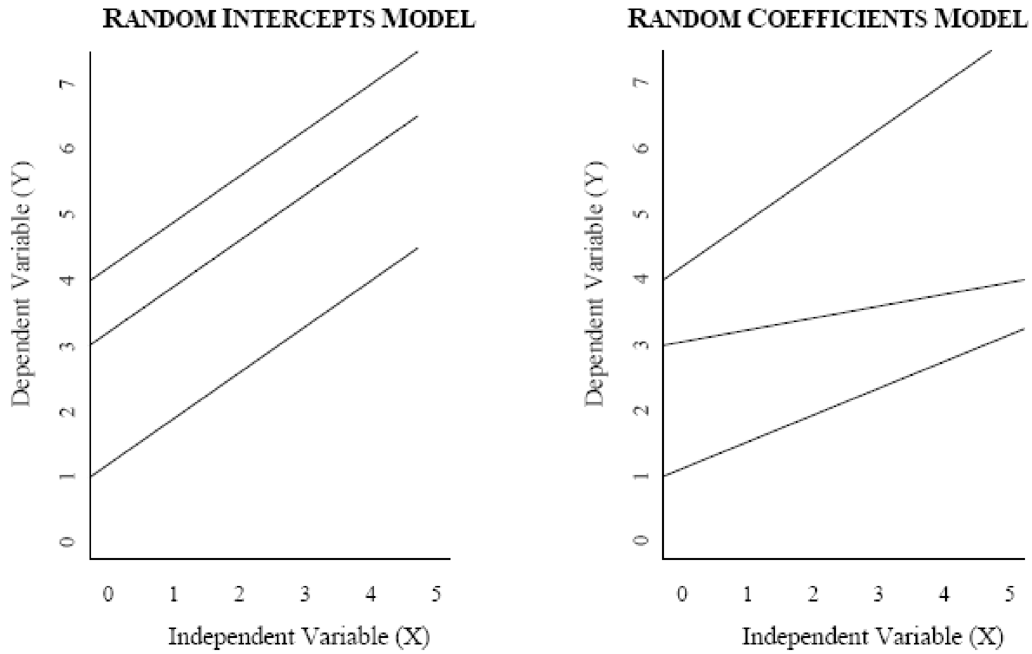


Figure 6: Cross Level Interaction of Offense Severity and Southern Location

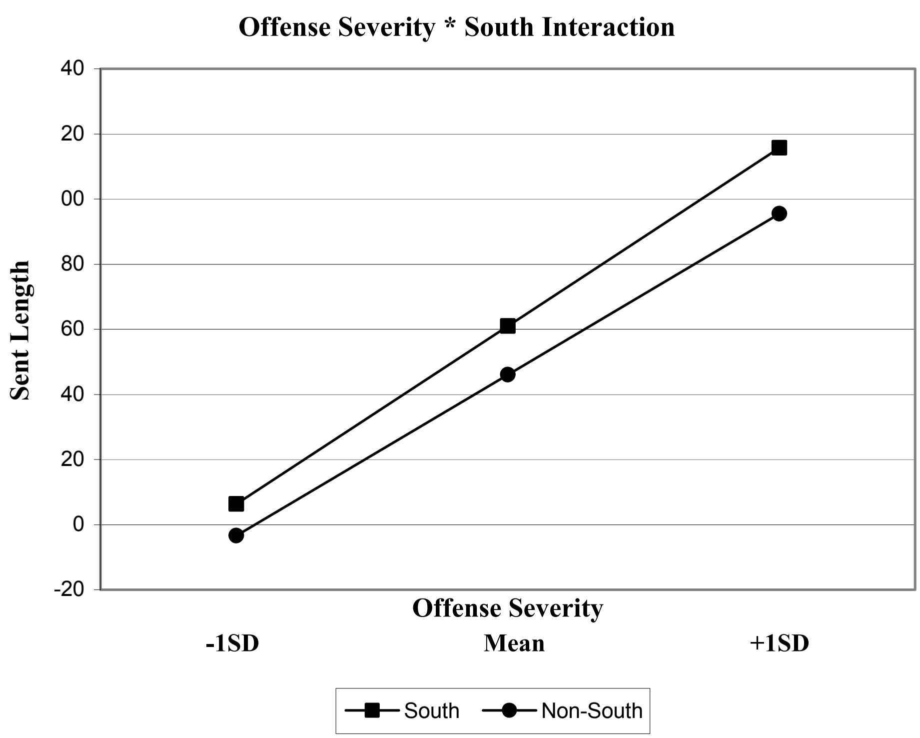


Table 1: Recent Examples of Multilevel Studies Published in *Crimin l gy* from 2005 to 2008

Author(s)	Year	Topic
Xie and McDowall	2008	Victimization and Residential Mobility
Schreck, Stewart, and Osgood	2008	Violent Offender and Victim Overlap
Johnson, Ulmer and Kramer	2008	Federal Guidelines Departures
Xie and McDowall	2008	Residential Turnover and Victimization
Mears, Wang, Hay and Bales	2008	Social Context and Recidivism
Zhang, Messner and Liu	2007	Crime Reporting in China
Kreager	2007	Sc ool Violence and Peer Acceptance
Wilcox, Madensen and Tillyer	2007	Guardianship and Buglary Victimization
Chiricos, Barrick, Bales, and Bontrager	2007	Labeling and Felony Recidivism
Osgood and Shreck	2007	Stability and Specialization in Violence
Rosenfeld, Fornango, and Rengifo	2007	Order-Maintenance Policing and Crime
Bernburg and Thorlindsson	2007	Community Structure and Delinquency
Warner	2007	Social Context and Calls to Police
Hay and Forrest	2006	T e Stability of Self-Control
Doherty	2006	Self-Control, Social Bonds, and Desistence
Griffin and Wooldredge	2006	Sex Disparities in Imprisonment
Sampson, Laub, and Wimer	2006	Marriage and Crime Reduction
Ulmer and Bradley	2006	Trial Penalties
Johnson	2006	Judge and Court Context in Sentencing
Kubrin and Stewart	2006	Neig borhood Context and Recidivism
Simons, Simons, Burt, Brody, and Cutrona	2005	Collective Efficacy, Parenting and Delinquency
Slocum, Simpson, and Smit	2005	Strain and Offending
Wright and Beaver	2005	Parental Influence and Self-Control
Bontrager, Bales, and Chiricos	2005	Race and Adjudicated Guilt
Kleck, Sever, Li, and Gertz	2005	Perceptions of Punishment
Johnson	2005	Sentencing Guidelines Departures

Table 2: Glossary of Multilevel Modeling Terminology

Terminology	Definition
Aggregate Variable	Ecological variable created by aggregating t e individual properties of lower level measures up to t e group level of analysis. Also sometimes referred to as "Derived" or "Analytical" variables.
Atomositic Fallacy	T e fallacy, also referred to as t e Individualistic Fallacy, t at results w en faulty inferences for macro level group relations ips are drawn using micro-level individual data. See Ecological Fallacy
Compositional Effects	Between group differences in outcomes t at are attributable to differences in group composition, or in t e different individuals of w ic t e groups are comprised.
Contextual Analysis	Early analytical approac designed to investigate t e effects of aggregate c aracteristics of t e collective by including aggregate variables along wit individual variables in traditional regression models.
Contextual Effects	Macro-level influences exerted by aggregate variables above and beyond t ose attributable to compositional differences in groups, but sometimes t e term is used to refer to any group level effects.
Contextual Effects Model	Statistical model t at include individual c aracteristics and t e aggregates of t e individual c aracteristics in t e same model in order to assess t e influence of contextual effects on individual outcomes.
Cross-Level Interaction	A statistical interaction between ig er and lower order variables, usually attempting to explain variation in t e effects of lower level measures across ig er level groupings.
Cross Classified Model	A multilevel statistical model for analyzing data t at is cross-nested in two or more ig er levels of analysis w ic are not strictly ierarc ical in structure. Also referred to as cross-nested models.
Ecological Fallacy	T e fallacy t at results w en faulty inferences for individual level relations ips are made using group level data. (see Atomistic Fallacy)
Ecological Variable	A broad term for any ig er order group level variable, including aggregate, structural and global measures. Sometimes referred to as a Group Level, Macro Level, or Level 2 variables.
Empirical Bayes Estimates	Estimates for group level parameters t at are optimally weig ted to combine information from t e individual group itself wit information from ot er similar groups in t e data. See Conditional S rinkage.
Fixed Effects	Regression coefficients (or intercepts) t at are not allowed to vary randomly across ig er level units. T ese are sometimes referred to as fixed coefficients. See Random Effects/Coefficients.
Fixed Effects Models	Statistical models in w ic all all effects or coefficients are fixed. Often t is refers to t e case w ere a dummy variable is included for eac ig er level unit to remove between-group variation in t e outcome.

Global Variable	A group level variable t at unlike Aggregate Variables as no individual analogue. Global (or Integral) Variables refer to c aracteristics t at are uniquely defined at t e ig er level of analysis.
Group Level Variable	An alternative name for ecological variables t at measure any group level c aracteristic. Sometimes referred to as Level 2 Variables. See Individual Variable.
Hierarc ical (Linear) Model	A multilevel model for analyzing data t at is nested among two or more ierarc ies. Hiearc ical models tec nically assume t at data are strictly nested across levels of analysis, alt oug t is term may refer to multilevel models generally.
Individual Level Variable	A variable t at c aracterizes individual attributes or refers to individual level constructs. Sometimes referred to as Level 1 Variables. See Group Level Variable.
Intraclass Correlation	T e proportion of t e total variance in t e outcome t at exists between groups or ig er level units rat er t an wit in groups or ig er level units.
Mixed Model	A multilevel model containing bot fixed and random coefficients. Some regression coefficients are allowed to vary randomly across ig er level units w ile ot er regression coefficients are specified as fixed coefficients.
Multilevel Analysis	An analytical approac for simultaneously analyzing bot individual and group level effects w en data is measured at two or more levels of analysis wit lower level (micro) observations nested wit in ig er level (macro) units.
Multilevel Model	A statistical model used in multilevel analysis for analyzing data t at is measured at two or more levels of analysis, including but not limited to ierarc ical linear models, iearc ical nonlinear models, and cross-classified models.
Population Average Estimates	Estimates for nonlinear multilevel models t at provide t e marginal expectation of t e outcome averaged across all random effects rat er t an after controlling for random effects. See Unit-Specific Estimates
Random Coefficient Model	A multilvel statistical model in w ic t e individual level intercept and regression coefficients are allowed to ave randomly varying effects across ig er level units of analysis. See Random Intercept Model.
Random Effects	Regression coefficients (or intercepts) t at are allowed to vary randomly across ig er level units. T ese are sometimes referred to as random intercepts or random coefficients. See Fixed Effects.
Random Intercept Model	A multilevel statistical model in w ic t e individual level intercept is allowed to vary randomly across ig er level units of analysis, but t e individual level coefficients are assumed to ave constant effects. See Random Coefficient Model.
Unit Specific Estimates	Estimates for nonlinear multilevel models t at are conditional on ig er level random effects. Unit specific models provide individual estimates controlling for rat er t an averaging across random effects. See Population Average Estimates
Variance Components	Model parameters (sometimes referred to as random effects) t at explicitly capture bot wit in-group and between-group variability in outcomes. Eac level of analysis in a multilevel model as its own variance component.

Table 3: Unconditional HLM Model of Federal Sentence Lengths

Sentence Length in Months							
	Fixed Effects		b	S.E.	df	p-value	
		Intercept (γ_{00})	52.5	1.8	88	0.00	
	Random Effects		s^2	S.D.	df	p-value	ρ
		Level 1 (r_{ij})	4630.0	68.0			
		Level 2 (u_{oj})	267.1	16.3	88	0.00	0.055
	Deviance = 282173.7						
	Parameters = 2						
	N=25,000						

Table 4: Random Intercept Model of Federal Sentence Lengths

Sentence Length in Months						
	Fixed Effects		b	S.E.	df	p-value
		Intercept (γ_{00})	51.0	1.1	88	0.00
		Severity (β_1)	5.6	0.2	24998	0.00
	Random Effects		s^2	S.D.	df	p-value
		Level 1 (r_{ij})	2228.7	47.2		
		Level 2 (u_{oj})	93.2	9.7	88	0.00
	Deviance = 263875.9					
	Parameters = 2					
	N=25,000					

Table 5: Random Intercept Model of Federal Sentence Length

Sentence Lengt in Mont s

Fixed Effects	b	S.E.	df	p-value
Intercept (γ_{00})	50.9	1.0	87	0.00
Sout (γ_{01})	7.1	2.3	87	0.00
Severity (β_1)	5.6	0.2	24997	0.00

Random Effects	s^2	S.D.	df	p-value
Level 1 (r_{ij})	2228.7	47.2		
Level 2 (u_{oj})	82.4	9.1	87	0.00

Deviance = 263860.9

Parameters = 2

N=25,000

Table 6: Random Coefficient Model of Federal Sentence Length

Sentence Lengt in Mont s

Fixed Effects	b	S.E.	df	p-value
Intercept (γ_{00})	49.7	1.0	88	0.00
Severity (β_1)	5.7	0.1	88	0.00

Random Effects	s^2	S.D.	df	p-value
Level 1 (r_{ij})	2098.7	45.8		
Level 2 (u_{oj})	78.7	8.9	88	0.00
Severity (u_{1j})	1.4	1.2	88	0.00

Deviance = 262530.1

Parameters = 4

N=25,000

Table 7: Comparison of OLS, Random Intercept and Random Coefficient Models

OLS REGRESSION

Without Robust Errors

	b	S.E.
Intercept	47.9	0.30
Offense Severity	5.6	0.03

RANDOM INTERCEPT

Without Robust Errors

	b	S.E.
Intercept	51.0	1.10
Offense Severity	5.6	.03

With Robust Errors

	b	S.E.
Intercept	51.0	1.06
Offense Severity	5.6	.19

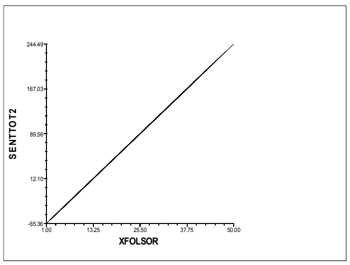
RANDOM COEFFICIENT

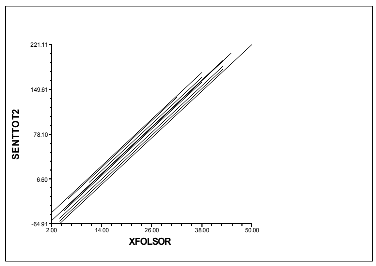
Without Robust Errors

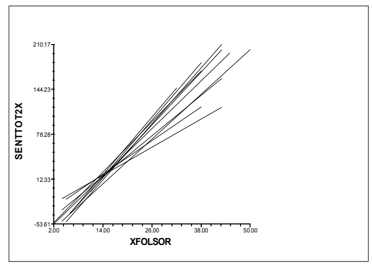
	b	S.E.
Intercept	49.7	1.02
Offense Severity	5.7	.13

With Robust Errors

	b	S.E.
Intercept	49.7	1.01
Offense Severity	5.7	.13







Random Intercept: Deviance = 263875.9
Parameters = 2

Random Coefficient: Deviance = 262530.1
Parameters = 4

Table 8: Random Coefficient Model with Level 2 Predictor of Federal Sentence Length

Sentence Length in Months

Fixed Effects	b	S.E.	df	p-value
Intercept (γ_{00})	49.6	1.0	87	0.00
South (γ_{01})	3.4	1.4	87	0.02
Severity (β_1)	5.7	0.1	88	0.00

Random Effects	s^2	S.D.	df	p-value
Level 1 (r_{ij})	2098.6	45.8		
Level 2 (u_{oj})	71.6	8.5	87	0.00
Severity (u_{1ja})	1.5	1.2	88	0.00

Table 9: Cross-Level Interaction Model of Federal Sentence Length

Sentence Lengt in Mont s

Fixed Effects	b	S.E.	df	T-ratio	p-value
Intercept (γ_{00})	49.6	1.0	87	49.14	0.00
Sout (γ_{01})	6.3	2.0	87	3.37	0.02
Severity (β_1)	5.7	0.1	88	42.45	0.00
Sout *Severity (γ_{11})	0.6	0.3	87	2.07	0.04

Random Effects	s^2	S.D.	df	χ^2	p-value
Level 1 (r_{ij})	2098.6	45.8			
Level 2 (u_{oj})	70.2	8.4	87	1130.14	0.00
Severity (u_{1j})	1.4	1.2	88	1644.40	0.00

Deviance = 262519.3

Parameters = 4

N=25,000

Table 10: Multilevel Logistic Model of Federal Incarceration

Prison vs. No Prison (Unit-Specific Model with Robust Standard Errors)

Fixed Effects	b	S.E.	df	p-value	Odds Ratio
Intercept (γ_{00})	2.80	0.08	87	0.00	
South (γ_{01})	0.07	0.11	87	0.53	1.07
Severity (β_1)	0.26	0.01	88	0.00	1.29

Random Effects	s^2	S.D.	df	p-value
Level 2 (u_{0j})	.41	0.64	87	0.00
Severity (u_{1j})	.004	0.06	88	0.00

Table 11: Three-Level Unconditional Model of Federal Sentence Length

Sentence Lengt in Months

Fixed Effects	b	S.E.	df	p-value	
Intercept (γ_{000})	52.5	3.2	10	0.00	
Random Effects	s^2	S.D.	df	p-value	ρ
Level 1 (e_{ijk})	4630.1	68.0			
Level 2 (r_{0jk})	172.5	15.2	78	0.00	0.035
Level 3 (u_{00k})	85.2	9.2	10	0.00	0.017

Table 12: Three-Level Mixed Model of Federal Sentence Length

Sentence Lengt in Months

Fixed Effects	b	S.E.	df	p-value
Intercept (γ_{000})	48.6	1.6	10	0.00
Sout (β_{01k})	2.8	1.7	87	0.10
Severity (π_{1jk})	5.7	0.2	10	0.00
Random Effects	s^2	S.D.	df	p-value
Level 1 (e_{ijk})	2098.6	45.8		
Level 2 (r_{0jk})	53.6	7.3	77	0.00
Severity (r_{1jk})	1.1	1.1	78	0.00
Level 3 (u_{00k})	17.6	4.2	10	0.00
Severity (u_{10k})	0.3	0.5	10	0.00

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