A NEW METHOD FOR STUDYING THE EXTENT, STABILITY, AND PREDICTORS OF INDIVIDUAL SPECIALIZATION IN VIOLENCE*

D. WAYNE OSGOOD
Department of Sociology
Pennsylvania State University

CHRISTOPHER J. SCHRECK
Department of Criminal Justice
Rochester Institute of Technology

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Specialization in violence is an important scientific and policy topic, and over the past several decades, many analysis techniques for studying specialization have emerged. Research in this area continues to be hampered, however, by remaining methodological problems. To overcome these problems, we propose a new method for studying specialization in violence based on an item-response theory measurement approach that is implemented through a multilevel regression model. Our approach defines specialization as an individual level latent variable, takes into account the inherent confounds between specialization and overall level of offending, and gauges specialization relative to the population base rates of each offense. Our method also enables

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researchers to 1) estimate the extent and statistical significance of specialization, 2) assess the stability of specialization over time, and 3) relate specialization to explanatory variables. Using data from three studies, we found substantial levels of specialization in violence, considerable stability in specialization over time, and several significant and relatively consistent relationships of specialization to explanatory variables such as gender, parental education, and risk-seeking.

Whether criminal offenders specialize in certain types of crime is a question of great interest for policy makers and scholars. If specialization exists, then it may be possible to improve the justice system through practices such as selective detention and targeted treatment (Tracy and Kempf-Leonard, 1996). Offense specialization also concerns the very nature of involvement in crime, and accordingly, many authors have argued that evidence of offense specialization carries strong implications for criminological theory (Bursik, 1980; Kempf, 1987; Piquero, 2000). For instance, if no specialization exists, then a single general explanation of offending, such as self-control theory (Gottfredson and Hirschi, 1990) or social control theory (Hirschi, 1969), could suffice to account for all types of crime (Osgood et al., 1988). In contrast, specialization is implicit in theories that either posit distinct types of offenders (Cloward and Ohlin, 1960; Colvin and Pauly, 1983) or that offer an explanation specific to a single type of crime, such as violence (R. Felson, 2002; Tedeschi and Felson, 1994; Wolfgang and Ferracuti, 1967).

Our research focuses on specialization in violence. Both citizens and policy makers have special concerns about violent crime, and the choice of effective justice system responses to address it depends on whether violent offenders differ meaningfully from other offenders. The National Research Council Panel on the Understanding and Control of Violent Behavior posed the question, "Are violent offenders merely frequent offenders?" (Reiss and Roth, 1993: 376). Several studies have found no significant difference (Capaldi and Patterson, 1996; Farrington, 1991; Piquero, 2000); yet others report at least some specialization in violence and some distinct features of violent offenders (Deane, Armstrong, and Felson, 2005; Lynam, Piquero, and Moffitt, 2004; Moffitt, Mednick, and Gabrielli, 1989).

Offense specialization refers to systematic individual differences in the types of crimes offenders commit. The primary focus of research on this topic has been discovering whether any more specialization exists than would be expected by chance alone. Research to date is disappointingly unclear on this point. Scant evidence of specialization can be found among samples of juveniles (Armstrong and Britt, 2004; Bursik, 1980; Rankin and Wells, 1985; Rojek and Erickson, 1982; Wolfgang, Figlio, and Sellin, 1972).

Research on adult offenders has yielded modest support for specialization, which most often appears for violence (Blumstein et al., 1988; Brennan, Mednick, and John, 1989; Britt, 1996). Yet other studies have reported that adults specialize in fraud (Brennan, Mednick, and John, 1989) and in serious property and drug offenses (Britt, 1996). When studies have found some specialization by juvenile offenders, it has mainly been for property and status offenses (Farrington, Snyder, and Finnegan, 1988; Kempf, 1987; Paternoster et al., 1998). Studies investigating the role of race and gender in specialization have reported inconsistent results about which groups are more likely to specialize and in which types of offenses they specialize (Blumstein et al., 1988; Bursik, 1980; Farrington, Snyder, and Finnegan, 1988; Lattimore, Visher, and Linster, 1994; Mazerolle et al., 2000). Although the evidence for specialization is weak, research has not yet been able to rule specialization out.

Research on specialization in offending has been limited by difficult methodological problems, as we will discuss below, and we believe that additional analytic tools designed to address these problems could significantly advance the study of this topic. The current article offers a new method for investigating specialization in violence and illustrates its use. Our method expands the range of data that can be used to investigate specialization, resolves some difficulties limiting previous approaches, and yields a variety of useful results. We begin by reviewing methodological challenges facing research on specialization and by noting several important advances in methods over the years. We then describe our new method and emphasize the ways in which it builds on prior work and addresses important challenges for research in this area. The subsequent section presents research applying this approach to self-report offense data for three samples, which together span the age range of 12 to 18 years.

ISSUES IN SPECIALIZATION RESEARCH

CONCEPTUALIZING SPECIALIZATION: SEQUENCE VERSUS DIVERSITY

Sequential Specialization

Researchers have sought evidence of specialization in two different aspects of patterns of offenses by an individual. The first of these aspects is the sequence of offenses, exemplified in Paternoster and colleagues' (1998: 133) definition of specialization as "the extent to which an offender tends to repeat the same specific offense or offense type on successive criminal events." Committing two consecutive robberies, for example, would indicate specialization, whereas switching to burglary after a robbery would reflect versatility or generality in offending. Early research on specialization focused on sequences of offenses (Blumstein and Larson, 1969; Wolfgang, Figlio, and Sellin, 1972), as do many current studies (Armstrong and Britt, 2004). Farrington's (1986) forward specialization coefficient (FSC) provides a popular index of sequential specialization, which expresses the tendency to repeat a given offense type on a scale of 0 to 1 (Farrington, Snyder, and Finnegan, 1988; Kempf, 1987; Paternoster et al., 1998; Piquero et al., 1999). Britt (1996) proposed a more elaborate alternative based on the analysis of mobility tables in research on stratification.

Although sequential analyses are useful and appropriate, they have three inherent limitations. First, sequential analysis requires time-ordered data, which is typically available for official records such as arrest or conviction histories but not for self-reports of offending. From our perspective, knowledge about offense specialization will be best enhanced by a portfolio of studies using both measurement approaches (Capaldi and Patterson, 1996; Farrington, 1991; Lynam, Piquero, and Moffitt, 2004). Self-report data overcome important weaknesses of official data because they are independent from police discretion and victim willingness to report to the authorities. Therefore, this method will provide more extensive information about offense histories than official records and could well avoid biases in assessments of specialization.[1]

Second, sequential analysis is also limited because it focuses only on similarity between offenses that are temporally adjacent and ignores useful information about similarities between other offenses (Bursik, 1980). For instance, sequential analyses will detect some specialization in the repeated robbery in the sequence robbery–robbery–burglary but not in the very similar sequence robbery–burglary–robbery. The inability to consider the larger offense pattern both reduces the precision of sequential analyses and underestimates the extent of specialization.

Third, the sequential approach estimates specialization only for aggregates, not for individuals (Mazerolle et al., 2000). Sequential analyses of specialization derive from transition matrices, which are cross-tabulations in which the rows indicate what type of offense was committed first (assault, robbery, etc.) and the columns indicate what type of offense was committed next. Because specialization implies repeating the same type of offense, it will be evident in a concentration of cases in the diagonal of this matrix. Only aggregate analysis is possible because data must be combined across many individuals to generate transition matrices with cell counts

1. Sequence is sometimes problematic for official records as well, for instance, if a single arrest entails multiple charges (e.g., burglary combined with disorderly conduct, assault, and resisting arrest). This ambiguity is often resolved by analyzing the most serious charge and by discarding useful information about the scope of the repertoire of the offender.

sufficient for a meaningful estimate of specialization. Later, we explain how this feature limits the value of this method for investigating the correlates of specialization.

Assessing Specialization Through the Variety or Diversity of Offenses

An alternative approach to studying specialization uses entire offense patterns and analyzes the variety of offenses each person commits (Farrington, 1991; Piquero et al., 1999). This approach infers specialization from the lack of variety, such as an offense record with a preponderance of violent crimes and a relative absence of other crimes. Versatility would be reflected in an offense record with a more diverse assortment of crimes.

Several studies have tested for offense specialization by comparing the observed proportions of cases with different mixtures of offenses to the proportions that would be expected by chance in the absence of any genuine differences in specialization. Most studies of this sort have addressed specialization in violence by computing expected proportions based on the binomial distribution and the overall percentages of violent and nonviolent offenses (Farrington, 1991; Lynam, Piquero, and Moffitt, 2004; Piquero, 2000). Like analyses of transition matrices, this approach defines specialization only for aggregates, not for individuals, but it has been successfully applied to both official data and self reports (Lynam, Piquero, and Moffitt, 2004).

Several recent studies focusing on the variety of offenses committed have used a diversity index that is similar to the FSC in calibrating specialization on a 0 to 1 scale (Mazerolle et al., 2000; Piquero et al., 1999; Sullivan et al., 2006). Specifically, this index reflects the probability that two randomly selected offenses drawn from the record of an offender will be of different types. Interestingly, the formula for this index is widely used to assess population diversity in community-level analyses and is the most common measure of ethnic heterogeneity in studies of social disorganization. For research on offense specialization, the index is computed separately for each individual. Researchers have used this method with official data (Mazerolle et al., 2000; Piquero et al., 1999) and self-reported offending (Sullivan et al., 2006).

An alternative source of information about the variety of offenses committed is the pattern of associations among various offenses, usually gauged by correlations among self-report offending items. Some early studies of specialization (Hindelang, 1971) focused on this aspect of offense patterns. Hindelang concluded that versatility dominated because correlations between items regarding the same type of offense (e.g., theft or assault) were not substantially stronger than correlations between items concerning different types of offenses. The reasoning underlying such analyses is that specialization is evident when offenders commit many varieties of a given type of offense (e.g., many forms of theft) and few or no offenses of other types. Although patterns of association such as these are the basis of most research on the closely related topic of the generality of deviance (Donovan and Jessor, 1985; Osgood et al., 1988), they have played a relatively small role in research on offense specialization. Indeed, although research on specialization using other types of data benefit from methodological tools such as the FSC and the diversity index, comparable tools have not been available for analyzing these patterns of association among offending items. We offer a method to fill this gap through a statistical approach that also applies to self-reported offending and defines specialization at the individual level.

CHALLENGES OF MEASURING INDIVIDUAL-LEVEL OFFENSE SPECIALIZATION

Although many studies of specialization have addressed only the existence of specialization, researchers have also shown considerable interest in identifying correlates of higher and lower levels of specialization. The FSC (Farrington, 1986) represented a major advance in sequential analyses of specialization because it provided a metric for the degree of specialization in a sample, thus enabling comparisons between groups such as males and females or offenders with longer and shorter criminal histories. Binomial analyses of specialization, for instance, have no such metric, so they are not useful for this purpose. Even so, the FSC is of limited value for relating specialization to explanatory variables because it assesses specialization only for aggregates. As a consequence, analyses of explanatory variables entail splitting the sample and running separate analyses. Considering more than one explanatory variable, such as asking whether a gender difference in specialization is attributable to differing offense rates, would require splitting the data multiple times (e.g., male and female and high-rate and low-rate offenders). Aggregate measures such as the FSC require large samples for stable estimates, however, which preclude fine-grain comparisons and limit researchers to very simple analyses of the correlates of specialization.

Defining specialization at the individual level overcomes these restrictions by providing a measure that can serve as the outcome variable in regression analyses, which thus enables a broad range of analyses that use multiple explanatory variables. Researchers have defined individual specialization in two ways. The simplest way has been to distinguish specialists and nonspecialists using ad hoc criteria. For instance, Capaldi and Patterson (1996) designated those arrestees ever charged with a violent offense as violent offenders and all others as nonviolent offenders, whereas Tracy and Kempf-Leonard (1996) considered people with more than half of their crimes falling into a single offense category to be specialists. The other approach has been to use the diversity index as a continuous measure of specialization (Mazerolle et al., 2000; Piquero et al., 1999; Sullivan et al., 2006). Although measuring specialization at the individual level has considerable advantages, existing approaches have three shortcomings.

1. *Specialization and offense rate*. Individual-level analyses of specialization are inextricably entangled with overall offense rates for two reasons. First, the more offenses a person commits, the more likely that at least one offense will be of any given type. Accordingly, dividing a sample into violent and nonviolent offenders based on whether they have committed at least one violent offense yields a much higher total-offense rate for the former than for the latter. As a result, a great deal of research has been devoted to determining whether any meaningful difference exists between violent offenders and frequent offenders (Farrington, 1991; Lynam, Piquero, and Moffitt, 2004). Second, the offense rates of individuals largely determine the precision with which we can assess their offense specialization because chance plays a more dominant role in the particular profile of offenses arising with 2 or 3 arrests than with 15 or 20. This issue applies to both ad hoc classifications and the diversity index.[2]

Studies comparing violent and nonviolent offenders, or specialists and nonspecialists, have addressed these issues by limiting analyses to individuals with some minimum total number of offenses (Capaldi and Patterson, 1996; Lynam, Piquero, and Moffitt, 2004) and using regression controls for total offending (Tracy and Kempf-Leonard, 1996). Unfortunately, these steps greatly reduce sample size and statistical power (e.g., Capaldi and Patterson, 1996, used 43 cases; Farrington, 1991, used 88 cases; and Piquero, 2000, used 59 cases) in return for only partially mitigating the confounding of offense rate and precision for the remaining cases. Resolving this issue would require a statistical model that uses all information for each person, assesses specialization independent from offense rate, and takes into account the dependence of precision on offense rate.

2. An example readily shows the dependence of precision on the number of offenses for the diversity index. The possible scores for the diversity index are determined by both the number of offenses recorded for an individual and the number of offense categories distinguished in the analysis. Consider the operation of the index in an analysis distinguishing ten offense categories. For a person with two offenses, the only possible diversity scores are 0, if the two offenses fall in the same category, and .5, if they fall in different categories. For a person with ten offenses, a score of 0 will occur only in the extreme circumstance that every offense is in a different category, and it rises modestly to .18 when a single category has two offenses.

2. *Offense base rates*. Methods used to study specialization generally gauge its presence by how much the concentration of offenses in a given category exceeds the base rate of that type of offense in the population. Suppose, for instance, that half of all offenses in a population were burglaries and that 5 percent were rapes. In that case, it is not specialization if half of the offenses by an individual are burglaries, which would be expected by chance, but it is specialization if half of the offenses are rapes.

Comparisons like this one, between observed offense proportions and offense base rates, are the essence of methods such as the FSC, Britt's (1996) alternative to the FSC, and binomial analyses of offense variety. In contrast, individual-level assessments of specialization have not yet succeeded in taking these base rates into account. For instance, Tracy and Kempf-Leonard (1996) identified specialists using the standard of 50 percent or more offenses in an offense category, which thereby invoked much stricter standards for specialization in less common offense categories than in more common ones. Although the diversity index provides a more sophisticated metric for individual-level analysis of specialization, it also fails to adjust for differences in base rates among offense categories. In fact, the formula for this index depends not at all on which offenses an individual commits. For instance, committing four offenses of one type and one each of four others will always produce a diversity score of .69 ($= 1 - [.5^2 + .125^2 + .125^2 + .125^2 + .125^2]$), whether the four offenses are in a common category, such as theft, or a rare category, such as sexual assault. Thus, the diversity coefficient does not correspond to the usual criminological conception of specialization, in which specialization is defined by the contrast between observed offense profiles and the proportions of offenses in the population.

3. *What type of specialization?* A final point for consideration in developing an individual-level index of specialization is whether one is interested in the extent that individuals specialize, without regard to the offense in which they specialize, or the degree to which they specialize in particular types of offending. Either issue constitutes a legitimate topic of inquiry, but they are nevertheless different topics. The diversity index concerns specialization in general in the sense that it reflects the degree to which offenses are concentrated in a few categories versus widely distributed across many. Thus, two individuals can show the maximum level of specialization through diversity scores of zero, with one committing only drug offenses and the other only assaults. A focus on this sense of specialization is useful for testing predictions about the general process of specialization, such as whether offenders tend to become more specialized with age (Britt, 1996; Farrington, 1991; Mazerolle et al., 2000).

An individual-level measure of specialization focused on a particular type of offense, such as violence, permits researchers to analyze what variables differentiate that type of offending from other types. We suspect that this topic is germane to more theoretical issues in criminology than the first, and it has been the primary concern of the sizable number of studies that have sought to distinguish violent offenders from other offenders. Farabee, Joshi, and Anglin (2001) made a comparable effort to distinguish specialists in victimless crimes from those who specialize in predatory crimes. The method we present below addresses specialization in violence rather than the extent of specialization in general.

REQUIREMENTS FOR A NEW METHOD FOR ANALYZING OFFENSE SPECIALIZATION

This review of previous research and available methods now leads us to seek the following attributes for a new method for studying offense specialization:

1. *Focus on the variety of offenses committed rather than on their sequence*. The emphasis of specialization research on transitions between subsequent offenses fails to capture the full information of the pattern of offending by an individual. Furthermore, the sequential approach requires information about the timing of all offenses, which is unavailable for many otherwise useful data sets.

2. *Apply to self-report measures of offending*. The study of specialization should include the wealth of information available in self-report studies rather than being limited to the truncated and potentially biased samples of offenses found in official records.

3. *Define specialization at the individual level to permit regression modeling*. Methods that define the extent of specialization for aggregates rather than for individuals effectively limit research on the correlates of specialization to bivariate relationships with simple categorical variables.

4. *Address the confounding between specialization and rate of offending*. A method for studying specialization needs to isolate specialization from the overall tendency to offend, to make use of available information for all sample members (rather than limiting analysis to a subset with some minimum number of offenses), and to take into account differences in precision of information about specialization that stem from variations in offense rate.

5. *Separate specialization from offense base rates*. Specialization in offending should be gauged by the contrast between an individual's concentration of offenses in certain offense categories and the overall rate of those offenses in the population.

A STATISTICAL MODEL FOR THE STUDY OF SPECIALIZATION

Next we present our statistical method for studying specialization in violent versus nonviolent offending, which incorporates all of these attributes. This method is founded on an item response theory (IRT) conception of measurement, which views the discrete data available in each item of a measure as probabilistically related to the latent construct of theoretical interest. Osgood, McMorris, and Potenza (2002) described the considerable advantages of the IRT framework for measuring self-reported offending. We follow Raudenbush, Johnson, and Sampson (2003) by implementing IRT measurement through multilevel regression modeling, and we take advantage of the flexibility of that approach to define specialization in violence independent of overall rate of offending.

At level 1, the more fine-grained level of analysis, our multilevel regression model specifies a measurement model that defines indices of both overall propensity to offend and specialization in violence. At level 2, the higher order unit of analysis, a structural model characterizes the resulting measures and relates them to explanatory variables. The level 1 unit of analysis is the response of an individual to a specific item, and the level 2 unit of analysis is the individual respondent. As we will explain, integrating these two levels of analysis in a single model enables us to define and study specialization as a latent variable in a way that addresses the issues we have raised.

We specify our model using the notation of hierarchical linear modeling (HLM) (Raudenbush and Bryk, 2002) to make clear the distinction between the measurement model and the structural model. Our level 1 regression equation is:

$$Log[odds(Y_{ij}=1)]=\beta_{0j}+\beta_{1j}Spec+\sum_{i=2}^{I}\beta_{ij}D_{ij} \qquad [1]$$

The level 2 regression equations are:

$$\beta_{0j}=\gamma_{00}+\gamma_{01}X_{1j}+\gamma_{02}X_{2j}+\ldots+u_{0j} \qquad [2]$$

$$\beta_{1j}=\gamma_{11}X_{1j}+\gamma_{12}X_{2j}+\ldots+u_{1j} \qquad [3]$$

$$\beta_{ij}=\gamma_{i0} \qquad [4]$$

The level 1 equation serves as the IRT measurement model, and as in all hierarchical linear models, it establishes the meaning of the level 2 equations. The level 1 outcome measure is the response of individual j to item i, with each item referring to a different illegal act. When a respondent j reports having committed offense i, then $Y_{ij} = 1$, and when that respondent reports that he or she did not do so, then $Y_{ij} = 0$.

The essence of the IRT measurement approach is that nonlinear link functions relate the probabilities of the possible responses for each item to the latent variables that are being measured. In equation 1, the logistic transformation on the left-hand side of the equation serves this purpose; it indicates that the model is linear in relation to the log odds of committing an offense and, thus, a nonlinear function of the probability. We chose the logistic link function (and the Bernoulli probability distribution that it implies) because we are treating the responses to our self-report measures as dichotomous.

Relying on dichotomous data means that our analyses focus strictly on the variety of offenses committed. The frequency with which different offenses are committed could be incorporated in our model by analyzing ordered response categories or frequency responses through ordinal logistic or Poisson versions of the model. These alternatives are available in current versions of most multilevel regression programs.

OVERALL OFFENDING

In equation 1, the log odds (and thus probability) that an individual will report having committed each offense depends on three factors. The first is the constant term of the equation, β_{0j}, which applies equally to all items. This coefficient varies randomly across individuals, as indicated by the residual term in its level 2 equation (u_{0j} of equation 2). Accordingly, β_{0j} captures individual differences in the rate of offending across all items. Furthermore, this variable is latent rather than directly observed, so it corresponds to the general tendency of an individual to offend, which is probabilistically manifested in his or her patterns of offenses (Rowe, Osgood, and Nicewander, 1990). Thus, this dimension corresponds to a general propensity to offend in the generic sense proposed by Rowe, Osgood, and Nicewander (1990: 241): "whatever constellation of factors determines the likelihood that an individual will engage in crime." The variance of the residual term u_{0j}, denoted τ_{00}, reflects the extent of individual differences in overall offending. The amount of variance is dependent on the degree to which committing any one offense is associated with a higher probability of committing all other offenses.

ITEM BASE RATES

The second factor contributing to the probability that an individual will commit a given offense is the base rate of that offense. The parameters β_{ij} capture differences in base rates among the items in the log odds metric. Relatively rare offenses, which typically are more serious as well (Osgood, McMorris, and Potenza, 2002; Raudenbush, Johnson, and Sampson, 2003), will have lower values of $\beta_{ij,}$ and more common offenses will have higher values. These parameters are incorporated in the model through a series of dummy variables coded to reflect which item is associated with each response (i.e., a value of 1 for that dummy variable and 0s for all others). We omit the dummy variable for one item in order to define the level 2 intercept term for overall offending. Note that the level 2 equations for these base-rate parameters (equation 4) do not include residual terms; this omission is consistent with their purpose of adjusting for differences in the rates at which various items are committed by the entire sample. Thus, the individual-level version of this term β_{ij} is equal to the population version γ_{i0}.[3]

SPECIALIZATION

The critical feature of our model is our definition of specialization in violent versus nonviolent offenses as a third factor determining the probability of committing each offense. We give this meaning to β_{1j} by coding the variable *Spec* so as to capture the contrast between responses to violent items and responses to nonviolent items. To accomplish this goal, we give *Spec* a positive value for items referring to violent offenses and a negative value for items referring to nonviolent offenses. Respondents who specialize in violence will report committing more violent offenses than nonviolent offenses. This pattern corresponds to a higher log odds of offending for items with positive values on *Spec* and, thus, yields a positive value on β_{1j}. Conversely, committing many nonviolent offenses and few violent offenses will produce a higher log odds for nonviolent acts and a negative value on β_{1j}. As with β_{0j}, the level 2 equation for β_{1j} includes a residual term (u_{1j} of equation 3), which makes this index of specialization a latent variable that varies across respondents. The absence of an intercept term in equation 3 makes 0 the mean of the specialization index, which is a value that will reflect a balance of violent and nonviolent offenses that corresponds to their base rates in the sample.[4]

The extent to which respondents systematically differ in emphasizing violent versus nonviolent offenses will be captured by the variance of u_{1j}

3. Explanatory variables can be added to equation 4 to allow for the possibility that the base rate of a specific item might vary in relation to factors extraneous to the concept of interest. For example, an item asking about damaging property at work is more relevant to those respondents who are employed than to those who are not, quite apart from their overall propensities to offend. Adding to equation 4 a measure of whether a respondent is employed avoids any distortion in the latent variables that would otherwise occur for this item. The analyses presented in this article used this approach for items referring to offenses at work in the Monitoring the Future analyses.

4. Omitting the intercept of equation 3 also maintains the original interpretation of the item parameters γ_{ij} as differences across items in the log odds of offending.

[τ_{11} in hierarchical linear modeling notation]. If differences in this emphasis are no greater than would be expected by chance, based on the other elements of the statistical model, then this variance will be close to zero and nonsignificant. Thus, our model provides a framework for assessing the existence and magnitude of specialization.

We avoid any inherent confound between this index of specialization and the overall tendency to offend by coding *Spec* to concern only the balance of violent and nonviolent items among the offenses individuals commit and not at all how many offenses they commit. We accomplish this goal by assigning *Spec* values that average to 0 for each person: For violent items *Spec* equals the proportion of items that concern nonviolent offenses, and for nonviolent items *Spec* equals minus the proportion of items that concern violent offenses.[5] These values guarantee that this variable has no variance across individuals, and as a result, *Spec* is not confounded with the overall level of offending by individuals (which is captured by the constant term β_{0j}). Furthermore, this index is adjusted for base-rate differences among items as a consequence of equation 4. Because these values for *Spec* result in a one-unit difference between violent and nonviolent items, β_{1j} provides an index of specialization calibrated to reflect the difference between the log odds of individuals committing a violent offense versus their log odds of committing a nonviolent offense.

The relationship between overall offending and the precision of information about specialization is inherent in this statistical model because individuals contribute to estimates about latent variables according to the precision available in their data (Raudenbush and Bryk, 2002: ch. 3). No information exists about specialization for respondents who commit either none of the offenses or all of them. Their log odds of offending are infinitely low or high for every offense, so no meaningful distinction can be made between their log odds for violent and nonviolent offenses. Respondents who report committing one or two offenses provide some information about whether they tend toward violent or nonviolent offenses but not much. With dichotomous data, the degree to which a person's offending emphasizes violent versus nonviolent offenses will be most evident for respondents who commit about half of the offenses. That case provides the most definitive contrast between those respondents who commit all of one type and none of the other and those respondents who commit about equal numbers of each. Our approach avoids the need to limit analysis to respondents who have committed some arbitrary minimum number of

5. The number of items may vary across individuals because of missing data at the item level. Note that this coding for *Spec* is equivalent to "group mean centering" in the HLM program for a dummy variable assigned 1 for violent items and 0 for nonviolent items.

offenses. Instead, analyses of the extent and correlates of specialization make appropriate use of the information provided by each respondent.

EXPLANATORY VARIABLES

Our multilevel model for the study of specialization also provides a framework for relating explanatory variables to both specialization and overall offending. This latent-variable approach is especially valuable for studying correlates of specialization because it takes into account the precision of specialization assessments, which vary widely across individuals. Analyses of individually computed scores, such as the diversity index, do not.

The level 2 equations 2 and 3 serve as structural regression models relating overall offending and specialization to substantive explanatory variables. The outcome variable of equation 2, β_{0j}, is the latent score of individual *j* for overall offending, whereas the outcome variable of equation 3, β_{1j}, is the latent score of individual *j* for specialization in violence versus nonviolence. A regression coefficient for overall offending, such as γ_{01}, indicates the increase in log odds of committing each offense that is associated with a one-unit increase in an explanatory variable (X_1 in this case). Similarly, a regression coefficient for specialization, such as γ_{11}, indicates the increase in specialization in violent versus nonviolent offenses associated with a one-unit increase in an explanatory variable (X_1). From the coding of *Spec*, the units of specialization reflect the extent to which log odds of violent offenses exceed those of nonviolent offenses, when adjusted for base-rate differences across all items. Thus, if higher scores on X_1 coincide with a predominance of violent over nonviolent offenses, γ_{11} will be positive; if they coincide with a predominance of nonviolent offenses, γ_{11} will be negative. As with all regression models, the γ regression coefficients of equations 2 and 3 express relationships that adjust (or control) for any other explanatory variables included in an equation.[6]

It is useful to compare our approach for incorporating explanatory variables with other multilevel logistic models that have been used for investigating the distinctive correlates of violent offending. Although Deane et

6. Osgood, McMorris, and Potenza (2002) present an approach that combines scoring self-reported delinquency through item-response analysis and relating the resulting scores to explanatory variables through Tobit analysis (Osgood, Finken, and McMorris, 2002). The model proposed here combines those steps into a single analysis. Standard IRT programs will not produce the scores for specialization in violence under our model because that variable is a contrast between positively correlated items. An HLM analysis could provide empirical Bayes estimates as scores for both latent variables. Those estimates could serve as outcomes measures in a Tobit regression analysis, provided that analysis was weighted to take into account the sizable variation in their precision.

al. (2005) were interested in specialization in violence, they did not define specialization or directly assess it. Instead, they examined relationships to explanatory variables separately for each item and inferred differential relationships to violence from those patterns. We have followed Raudenbush et al. (2003) in using an item-response model at level 1 to define composite measures, which we relate to explanatory variables at level 2. Unlike our approach, Raudenbush et al. formed separate composite latent variables for violent and property offending, so the correlates of specializing in violence must be inferred from the differences between relationships to the two types of offenses. Our alternative formulation more directly addresses the confounding between violence and the general propensity to offend by defining and modeling separate measures of overall offending and specialization in violence.

ADDITIONAL ASSUMPTIONS

Our measurement model falls into the class of IRT models known as Rasch or one- parameter models, which include one parameter for each item in order to allow for differences in base rates across items (β_{ij} in equation 1). As Raudenbush et al. (2003) explain, the one-parameter model is inherent in multilevel regression measurement models such as equation 1. A different statistical framework is necessary for IRT models that include a second parameter per item to allow for differences in the strength of their relationships to the latent construct being measured. Accordingly, our statistical model assumes that no substantial differences exist across items in their relationships to both overall offending and specialization.

The one-parameter model assumes that all items are equally related to the latent construct, which has considerable advantages for our aims. First, our strategy uses this assumption to define specialization by manipulating the direction of those relationships through the coding of *Spec*. Doing so would not be possible if the relationships varied freely. Second, the latent variable regressions relating specialization and overall offending to explanatory variables rely on the multilevel regression approach, which requires the assumption of equal relationships across items.

Of course, the results generated by our statistical model will not be meaningful if this assumption is poorly suited to the data. Raudenbush et al. (2003) demonstrated an approach to testing this assumption directly, but unfortunately, it does not apply to our model, which defines two distinct latent variables from the same set of items. We believe that several good indications show that the one-parameter model is appropriate for all three data sets we analyzed. First, consistent with the latent variable for overall offending, all items in each measure were positively correlated with one another and had high and relatively homogeneous loadings on a first factor in factor analyses. Second, consistent with the latent variable for specialization, violent items were more strongly associated with one another than with nonviolent items and vice versa. Finally, the only items Raudenbush et al. (2003) studied that were a poor fit to the one-parameter model were items about offending within the home: hitting someone you live with and stealing from a member of your own household. This pattern matches Huizinga and Elliott's (1986) finding that items such as "hitting someone in your family" were likely to elicit reports of trivial incidents. Our analyses include no such questions about offenses within the home, and we believe that the items we included were at least as homogeneous as those analyzed by Raudenbush et al.

To implement a multilevel regression model such as ours, it is also necessary to assume specific distributions for the residuals of the latent variables (u) and the standard for random effects models such as HLM is the multivariate normal distribution. This assumption is less problematic than it might appear at first glance. As Osgood and colleagues (Osgood, Finken, and McMorris, 2002; Osgood and Rowe, 1994; Rowe, Osgood, and Nicewander, 1990) have explained, nonlinear link functions, such as the logistic transformation in equation 1, can translate a normal distribution on a latent dimension to a decidedly skewed and discrete distribution of observed scores. Also, robust standard errors provide significance tests of regression coefficients (γ) that do not depend on this assumption (Raudenbush and Bryk, 2002: 276–78). Finally, current multilevel regression programs such as HLM include facilities to check for violations of the assumption of multivariate normality (Raudenbush and Bryk, 2002: 273–75), which revealed no problems for our analyses.

METHODS

The remainder of this article illustrates our approach to studying specialization in violence through analyses of three data sets, two of which provide measures of self-reported delinquency for the same sample at multiple ages. These data allow us to assess the consistency of findings across locations and age (respondents aged 12 to 18 years) as well as to assess the stability of specialization over time.

SAMPLES

MONITORING THE FUTURE

Our first data set comes from the Monitoring the Future study. This ongoing study began in 1975 and gathers a wide range of information annually from a nationally representative sample of high-school seniors through a three-stage national probability sample of approximately 130 high schools (roughly 110 public and 20 private). A random one sixth of each sample completes the version of the questionnaire that includes self-report delinquency. Our analyses include the high-school senior classes of 2002 through 2004, which include a total of 7,190 respondents. For a detailed description of the sample design and data collection, see Bachman, O'Malley, and Johnston (1991).[7]

Our analyses are based on 11 items concerning self-report delinquency in the past year, with the five possible responses ("not at all," "once," "twice," "three or four times," and "five or more times") recoded to 0 for none versus 1 for one or more times. Appendices A–C list the self-report delinquency items for each data set, along with the percent of respondents who reported committing each offense and the estimates of item seriousness or "difficulty" γ_{i0} from our statistical model.

We illustrate the use of explanatory variables in our statistical model with seven additional measures that have been of considerable interest to criminologists. The self-reported average high-school grades of respondents come from an item with response categories 1 for D or below, 2 for C–, and so on through 9 for A. The average education level of parents, as reported by respondents, is on a scale of 1 (grade school or less) to 6 (graduate or professional school). We coded gender as 0 for females and 1 for males and expressed race/ethnicity through two dummy variables for African-American and other nonwhites (with white as the reference category). Risk-seeking, which is a component of Gottfredson and Hirschi's (1990) concept of self-control, is reflected in a pair of items concerning preference for danger and risk, each on a 1 to 5 scale of disagree to agree. Unstructured socializing with peers is the mean of the four items that Osgood et al. (1996) identified in their application of the routine activities perspective to individual offending. Finally, we assess religiosity as the mean of a pair of items about the frequency of attending services and the importance of religion in the life of an individual.

Montreal Study

We use two waves of data from a study of French-speaking boys from low socioeconomic background in Montreal, Quebec, Canada (Tremblay et al., 1994). All boys were white, had parents who were born in Canada, and did not have any mental or physical disabilities. The Montreal study collected data on the respondents from kindergarten through high school. Our analyses are limited to the self-reports of the boys about their delinquent involvement at ages 12 ($n = 901$) and 17 ($n = 736$) years. The items asked respondents how many times they had committed each act in the

7. The analyses we report do not use the sample weights available for this data set because doing so precludes the significance test for specialization, which is essential to our aims. Weighted analyses produced virtually identical results, however, and all conclusions we report hold for the weighted results.

past 12 months and provided response choices of "never," "once or twice," "many times," and "very often." We recoded each item to a dichotomy of 0, did not commit the act during this period, versus 1, committed the act at least once.

G.R.E.A.T. Evaluation

Esbensen and colleagues' (2001) evaluation of the G.R.E.A.T. gang prevention program provides the final data set we use to illustrate our method for studying specialization in violence. This data set increases the scope of our analyses by adding an estimate of the stability of specialization in violence over a 1-year interval and a test of the consistency of regression results predicting specialization. We chose to analyze the third and fourth waves of the study, collected in grades 8 (n = 1,700) and 9 (n = 1,501), because rates of delinquency were quite low in earlier waves. This highly diverse sample is drawn from six cities in several different regions of the United States. Respondents indicated the absolute number of times they committed each delinquent offense in the past 6 months, which we recoded to a dichotomy of none versus one or more times. See Esbensen et al. (2001) for information about sample selection, data collection, and measures.

We selected explanatory variables from this data set that overlap with the Monitoring the Future data set as much as possible. Both include comparable measures of parental education, gender, and ethnicity (distinguishing the additional category of Hispanic in the G.R.E.A.T. data). No measure of school grades was available, so we included a measure of school commitment, instead. The G.R.E.A.T. evaluation assessed risk-seeking through the Grasmick et al. measure (1993) and provided a single-item measure of unstructured socializing, which we coded as described by Osgood and Anderson (2004). We also included in our analyses measures of parental monitoring and dangerous school environment, which are described by Esbensen et al. (2001).

A Note on Item Overlap

Our analyses of each data set excluded some self-report delinquency items that had a definite logical overlap with others. For instance, each data set included items concerning thefts of articles worth different ranges of monetary value, such as less than $50 and over $50, as well as other items asking about types of theft, such as shoplifting, theft from school, and burglary. Because any item stolen in a burglary has some dollar value, using both types of items would build in artificial relationships that would likely inflate estimates of specialization. To avoid this result, we omitted some items, in this case, those referring to dollar amounts.

Possibilities remain, however, that respondents could answer affirmatively to more than one item for a single offense, such as participating in a gang fight and using a weapon or trespassing and stealing a car part. We have no way of knowing how often this overlap happens or the degree to which such potential overlap would affect our estimates of specialization in violence. Interestingly, including the items with definite overlap did not increase estimates of specialization, which suggests that item overlap does not present serious problems. The issue would best be addressed, however, through careful construction of self-report inventories to ensure that respondents do not report the same offenses in response to multiple items.

ESTIMATION OF THE STATISTICAL MODEL

Our statistical model of specialization takes the form of a multilevel regression analysis with a logistic link function. Like Raudenbush, Johnson, and Sampson (2003), we found considerable underdispersion in our data (values ranging from .389 to .521, which correspond to z values ranging from 54 to 287 for comparisons with the neutral value of 1), which indicates violations of the IRT assumption of local independence. We follow their lead in addressing this issue by estimating our model using penalized quasi-likelihood (PQL) with underdispersion. Although PQL generally tends to underestimate variance components, we found that when we allowed for underdispersion the estimated variance components were roughly similar to those provided by full maximum likelihood (Raudenbush, Yang, and Yosef, 2000).

RESULTS

Our primary focus is to ascertain whether there are meaningful individual differences in the tendency to commit violent versus nonviolent offenses. Our statistical framework allows us to address this question in several ways, each of which illustrates a different aspect of the information provided by our approach.

THE STATISTICAL RELIABILITY OF INDIVIDUAL DIFFERENCES IN SPECIALIZATION

Ascertaining whether observed individual differences in specialization in violence are greater than would be expected by chance requires a significance test of the relevant variance component τ_{11}, which corresponds to the residual term u_{1j} of equation 3. For this purpose we are interested in the full variance of the latent variable for specialization, so we omit explanatory variables from the level 2 equations (equations 2 and 3). The standard significance test for this variance is a deviance test that compares models with and without this term, but this approach is only available with true maximum likelihood estimation, not PQL. We therefore rely on the more approximate z test obtained by dividing these estimates by their standard errors, both of which appear in table 1. Fortunately, the results of these z tests are definitive in all five tests, ranging from 9.0 for the Montreal sample, which had respondents aged 12 years, to 30.8 for the Monitoring the Future sample, which had respondents in grade 12 (aged 18 years), and all are statistically significant at well beyond the .001 level (two-tailed critical value of 3.3 for $\alpha = .001$). These results leave no doubt that individual differences in specialization in violence are greater than can be accounted for by chance alone.

Table 1. Reliability and Variance of Overall Offending and Specialization in Violence

	Overall Offending		Specialization	
Monitoring the Future	Grade 12		Grade 12	
Reliability	.74		.46	
Variance (τ)	4.26 (.09)		4.25 (.14)	
Montreal Study	Age 12	Age 17	Age 12	Age 17
Reliability	.78	.79	.39	.46
Variance (τ)	3.14 (.19)	3.57 (.23)	1.93 (.21)	2.56 (.26)
G.R.E.A.T. Evaluation	Grade 8	Grade 9	Grade 8	Grade 9
Reliability	.82	.81	.43	.47
Variance (τ)	4.44 (.18)	4.25 (.19)	2.30 (.17)	3.00 (.21)

NOTE: Standard errors of τ in parentheses.

Table 1 also provides reliability estimates that indicate how precisely the positions of respondents on overall offending and specialization were measured. The reliability of scores for overall offending ranges from .74 to .82, which is respectable by the usual standards of social science research. The reliability of specialization in violence is decidedly lower, with a high of .47 for respondents in grade 9 in the G.R.E.A.T. Evaluation and a low of .39 for respondents aged 12 years in the Montreal Study. The imprecision of scores on specialization results from the limited information inherent in the responses of most individuals. Most respondents reported committing few, if any, of the offenses, thus providing only a crude contrast between their rates for violent and nonviolent offenses. An accurate analysis of the correlates of specialization in violence requires a means of taking into account the limited reliability of individual specialization scores and the dependence of their precision on the offense rates of an individual, which our latent variable modeling approach provides.

THE MAGNITUDE OF INDIVIDUAL DIFFERENCES IN SPECIALIZATION

Our initial findings establish that statistically significant individual differences exist for specialization in violence and that we cannot measure degrees of specialization for individuals precisely. Yet those results neither indicate the magnitude of these individual differences nor make clear their implications for patterns of offending.

In multilevel models, the extent of individual differences is reflected in the variance components τ, which table 1 reports for both overall offending and specialization. For specialization, this variance estimate reflects the degree to which differences between rates of violent and nonviolent offenses vary across individuals over and above the variation that would be expected by chance alone. Variance in specialization ranges from 1.93 to 4.25, which constitutes anywhere from about half to all of the magnitude of variance in overall offending (2.30 for specialization vs. 4.44 for overall offending for respondents in the G.R.E.A.T. sample at grade 8; 4.25 vs. 4.26 for respondents in the Monitoring the Future sample at grade 12). These values suggest that specialization in violence makes a sizable contribution to individual offense patterns. Note that, consistent with earlier studies (Bursik, 1980; Piquero et al., 1999), specialization seems to increase somewhat with age (τ_{11} 1.93 at age 12 years vs. 2.56 at age 17 years for the respondents in the Montreal Study and 2.30 at grade 8 vs. 3.00 at grade 9 for the respondents in the G.R.E.A.T. Evaluation).

What do these variance estimates imply about patterns of offending? Our statistical model defines the units of specialization as log odds differences in the rates of violent versus nonviolent offenses. This definition implies that a unit of increase on this dimension multiplies the ratio of odds for violent offenses to the odds for nonviolent offenses by 2.71 (the exponential of 1). The largest variance estimate, for Monitoring the Future, is 4.26, which corresponds to a standard deviation of 2.06. Thus, in this sample, each standard deviation of increase in specialization in violence multiplies the odds of violent offenses by 7.86 (the exponential of 2.06), relative to the odds of nonviolent offenses. The smallest variance for specialization is 1.93 for respondents in the Montreal Study at age 12 years, which corresponds to an odds ratio of 4.01 per standard deviation. In other words, these variance estimates suggest substantial differences in the underlying tendencies toward violent versus nonviolent offending.

Table 2 provides an additional view of the extent of variation in specialization in violence that is a little closer to the data and less abstracted through the statistical model. This table compares the observed probabilities of committing violent and nonviolent offenses for respondents who tended toward violent offending (at least 1 standard deviation above the mean for specialization[8]), toward nonviolent offending (at least 1 standard deviation below the mean), or neither. Because estimates of specialization have a limited range for respondents who commit nearly all or none of the offenses, these calculations omit the 80 percent to 90 percent of respondents in each sample who commit fewer than about one third of the offenses and the 2 percent to 3 percent of respondents in each sample who commit more than about two thirds of them.

In all cases, very sizable differences between specialists in violence and specialists in nonviolent offenses emerged for rates of violent and nonviolent offenses. Specialists in violence committed 55 percent to 79 percent of the violent offenses but only 15 percent to 34 percent of the nonviolent offenses. Specialists in nonviolence committed only 8 percent to 26 percent of violent offenses but 53 percent to 77 percent of nonviolent offenses. These differences in rates correspond to odds ratios ranging from 33.9 for the G.R.E.A.T. Evaluation in grade 8 to 172.8 for Monitoring the Future. The magnitude of these differences is consistent with the estimated variance components for the latent variable of specialization and illustrates their implications. Our exploration of the variance components and corresponding offense patterns suggests that specialization in violence may be of greater substantive importance than has been previously recognized, which is consistent with the findings of Deane, Armstrong, and Felson (2005).

STABILITY OF SPECIALIZATION IN VIOLENCE

Two of our data sets include measures of offending at two ages, which allows us to assess the stability of specialization over time. We have no clear expectation that specialization in violence will be either highly stable or unstable. Even so, assessing stability provides additional evidence about the substantive importance of this variable. At least moderate stability would indicate that specialization in violence has a reality that endures over time, whereas an absence of stability would leave open the possibility that it is a momentary and perhaps ephemeral phenomenon.

We adopt the typical definition of stability as the correlation of a measure with itself over time. We estimated the stability of specialization through an expanded version of our statistical model that included overall offending and specialization on two occasions.[9] Multilevel regression analyses yield covariances among any latent variables (i.e., those with random

8. Here the standard deviation was compared to the HLM, non-Bayesian estimates of the individual values of u_{1j}. Bayesian estimates would necessarily produce more extreme results, so we chose the more conservative approach.
9. This model replaces the constant term of the level 1 equation (equation 1) with a pair of dummy variables indicating whether each item is from the first or second

Table 2. Observed Probabilities of Committing Violent and Nonviolent Offenses for Respondents Differing on Specialization in Violence

Monitoring the Future[a] **Grade 12** **Specialization**	**Observed Probability of Committing Offenses** Violent	Nonviolent	Total	*n*
Violent (> +1 SD)	.70	.25	.45	165
Medium (> –1 SD and < +1 SD)	.38	.49	.44	380
Nonviolent (< –1 SD)	.10	.73	.44	105

Montreal Study[b] **Age 12** **Specialization**	**Observed Probability of Committing Offenses** Violent	Nonviolent	Total	*n*
Violent (> +1 SD)	.64	.15	.46	27
Medium (> –1 SD and < +1 SD)	.44	.42	.43	96
Nonviolent (< –1 SD)	.26	.77	.45	29

Montreal Study **Age 17** **Specialization**	**Observed Probability of Committing Offenses** Violent	Nonviolent	Total	*n*
Violent (> +1 SD)	.79	.29	.47	30
Medium (> –1 SD and < +1 SD)	.50	.49	.50	44
Nonviolent (< –1 SD)	.18	.53	.40	21

G.R.E.A.T. Evaluation[c] **Grade 8** **Specialization**	**Observed Probability of Committing Offenses** Violent	Nonviolent	Total	*n*
Violent (> +1 SD)	.65	.34	.47	56
Medium (> –1 SD and < +1 SD)	.38	.47	.43	167
Nonviolent (< –1 SD)	.16	.64	.44	39

G.R.E.A.T. Evaluation **Grade 9** **Specialization**	**Observed Probability of Committing Offenses** Violent	Nonviolent	Total	*n*
Violent (> +1 SD)	.55	.32	.41	75
Medium (> –1 SD and < +1 SD)	.32	.51	.43	156
Nonviolent (< –1 SD)	.08	.67	.42	27

[a] Based on respondents who committed 4 to 7 of 11 offenses, who constituted the 89th to 98th percentiles for overall offending.

[b] For age 12 years, based on respondents who committed 4 to 7 of 11 offenses, who constituted the 81st to 97th percentiles for total offending. For age 17 years, based on respondents who committed 5 to 9 of 14 offenses, who constituted the 89th to 97th percentiles for total offending.

[c] Based on respondents who committed 4 to 8 of 12 offenses. This group constituted the 83rd to 97th percentiles for grade 8 and the 84th to 98th percentiles for grade 9.

variation across individuals). Standardizing these covariances in relation to the variance estimates yields correlation coefficients that are adjusted for error of measurement.

The correlations among the two sets of measures in the Montreal Study and the G.R.E.A.T. Evaluation appear in table 3. The stabilities of overall offending and specialization in violence are statistically significant for both studies (all z values greater than 4). Both estimates of stability for specialization are substantial, and not surprisingly, stability is higher over the 1-year interval we chose for the G.R.E.A.T. Evaluation (r = .43) than over the 5-year interval we chose for the Montreal Study (r = .39). Given that great substantive importance is widely attributed to the stability over time of individual differences in overall offending (Gottfredson and Hirschi, 1990; Moffitt, 1993), it is notable that overall offending is only moderately more stable than specialization in the G.R.E.A.T. Evaluation (r = .64) and no more stable in the Montreal Study (r = .38).

Table 3 also reveals a modest positive correlation between overall propensity to offend and specialization in violence in all samples except respondents aged 12 years in the Montreal Study. This result is difficult to interpret because the magnitude of the correlation varies considerably not only across ages but also across studies, which suggests that the correlation may depend on the specific violent and nonviolent acts included. Suffice it to say that the common finding that violence is more likely to appear on the records of high-rate offenders could possibly be more than a statistical artifact of their higher probability of committing all offenses (Farrington, 1991; Piquero, 2000).

THE RELATIONSHIP OF SPECIALIZATION TO EXPLANATORY VARIABLES

As a final means of assessing the substantive importance of specialization in violence, we examine the relationship of this latent variable to several explanatory variables. Our reasoning is simply that systematic relationships with other variables of interest to criminologists would further indicate that individual differences in specialization are meaningful.

Table 4 relates the explanatory variables to the latent variables of overall offending and specialization in violence for the Monitoring the Future sample, and table 5 does so separately for grades 8 and 9 of the

wave of data. The coefficients for those two variables are then the latent variables for overall offending at each wave. This model also has a level 1 coefficient for specialization in each wave of data. Because we remain interested in the full variance of the latent variables (rather than their residual variance), their level 2 equations omit any explanatory variables.

Table 3. Correlations Among Wave 1 and 2 Measures of Overall Offending and Specialization in Violence

Monitoring the Future Grade 12	**Overall Delinquency**
Specialization	.13*
	(.02)
	n = 7,190

Montreal Study	**Overall Delinquency**		**Specialization**	
	Age 12	**Age 17**	**Age 12**	**Age 17**
Overall Delinquency				
Age 17 years	.38*			
	(.05)			
Specialization				
Age 12 years	.03	.10		
	(.06)	(.06)		
Age 17 years	–.06	.13*	.39*	
	(.06)	(.06)	(.08)	
	n = 723			

G.R.E.A.T. Evaluation	**Overall Delinquency**		**Specialization**	
	Grade 8	**Grade 9**	**Grade 8**	**Grade 9**
Overall Delinquency				
Grade 9	.64*			
	(.04)			
Specialization				
Grade 8	.23*	.11*		
	(.04)	(.04)		
Grade 9	.13*	.32*	.43*	
	(.04)	(.04)	(.05)	
	n = 1,416			

NOTE: Standard errors in parentheses.
*$p < .05$.

G.R.E.A.T. Evaluation. These results are in the form of logistic coefficients (γ) from equations 2 and 3 of our statistical model. The coefficients for overall offending reflect the change in log odds of committing each offense that is associated with a one unit increase in the explanatory variable. As one would expect from the criminological research literature, in general, and prior analyses of the Monitoring the Future and G.R.E.A.T. data, in particular (Osgood and Anderson, 2004; Osgood, Finken, and McMorris, 2002; Osgood et al., 1996), almost all of these measures are strongly associated with overall offending for all three analyses.

The coefficients for specialization in violence indicate the relationship of an explanatory variable to the differential between violent versus nonviolent offending, independent of the overall level of offending of an individual and the base rate or seriousness of the offense. As with all regression coefficients, they reflect the change in the outcome measure associated

Table 4. Relationships of Explanatory Variables to Overall Offending and Specialization in Violence from a Logistic Hierarchical Linear Model, Monitoring the Future Data

	Overall Offending		Specialization in Violence	
	γ	SE	γ	SE
High-school grades (1–9)	–.09*	.007	.01	.008
Parental education (1–6)	.00	.010	–.06*	.011
Male (0–1)	.37*	.025	.05	.029
African American (0–1)	.33*	.043	.20*	.048
Other nonwhite (0–1)	.23*	.031	.07	.036
Risk-Seeking (1–5)	.19*	.013	–.08*	.013
Unstructured socializing (1–5.25)	.38*	.017	.05*	.018
Religiosity (1–4)	–.11*	.015	.05*	.016
		n = 7,190		

NOTE: γ is the HLM population average estimate, and SE is its robust standard error.
$*p < .05$.

with a one unit increase in the explanatory variable, and the units of this outcome variable are differences in log odds between the rate of violent offenses and the rate of nonviolent offenses. An additional interpretation

Table 5. Relationships of Explanatory Variables to Overall Offending and Specialization in Violence from a Logistic Hierarchical Linear Model, G.R.E.A.T. Evaluation Data

	Grade 8				Grade 9			
	Overall Offending		Specialization in Violence		Overall Offending		Specialization in Violence	
	γ	SE	γ	SE	γ	SE	γ	SE
School commitment	–.45*	.04	.09⁺	.05	–.46*	.04	.21*	.06
Parental education (1–6)	–.02	.02	–.02	.03	–.02	.02	–.08*	.03
Male (0–1)	.42*	.05	.20*	.06	.26*	.05	.28*	.06
African American (0–1)	.61*	.08	.09	.08	.59*	.07	.09	.10
Hispanic (0–1)	.29*	.07	–.03	.08	.53*	.07	–.36*	.08
Other nonwhite (0–1)	.08	.08	–.13	.09	.37*	.09	.00	.11
Risk-Seeking (1–5)	.35*	.03	–.09*	.03	.37*	.03	.01	.04
Unstructured socializing (1–7)	.16*	.02	.00	.02	.17*	.02	–.02	.02
Parental monitoring (1–5)	–.22*	.04	.04	.04	–.30*	.04	–.06	.05
Dangerous school environment (1–5)	.28*	.05	.16*	.05	.23*	.05	.07	.05
n		1,700				1,501		

NOTE: γ is the HLM population average estimate, and SE is its robust standard error.
$*p < .05$; $^{+}p = .054$.

of the coefficients for specialization would be that they indicate the difference between the relationship of the variable with violent offenses and its relationship with nonviolent offenses.

Are these explanatory variables predictive of specialization in violence? The results presented in tables 4 and 5 give a qualified answer of “yes.” Many statistically significant relationships with specialization appear in these tables, but those relationships are, on the whole, considerably weaker and less consistent than the relationships of the same variables with overall offending. No single relationship with specialization was significant in all three models, although several were in two of the three: school commitment and being male with more specialization in violence and parental education and risk-seeking with less specialization in violence. Overall, enough of the relationships are statistically significant, and the pattern of results is consistent enough for us to judge that these results support our general conclusion that individual differences in specialization in violence are genuine and substantively meaningful, if less so than overall involvement in delinquent behavior.

In considering these findings, it is important to remember that the latent variable for specialization in violence reflects only the relative balance of violent and nonviolent offending, and not the amount of offending. For instance, the negative association between religiosity and overall offending does not contradict its positive association with specialization in violence. These results mean that people who are more religious are less likely to offend, in general, but when they break the law, it is more likely to be for a violent offense than for a nonviolent one. As a result, it should not be surprising that the pattern of relationships for specialization is entirely different than the pattern for overall offending. Parental education, the one variable not associated with overall offending, is associated with specialization toward nonviolent offenses. Furthermore, tables 4 and 5 include both examples in which variables significantly associated with specialization in violence are related to overall offending in the same direction (gender and African-American race/ethnicity) and examples in which they are related to overall offending in the opposite direction (risk-seeking and religiosity). Clearly, the tendency to specialize in violence is distinct from the overall propensity to engage in crime.

The differences in findings among the three models in tables 4 and 5 make it hard to draw strong conclusions about which factors are important correlates of specialization in violence. For the most part, differences in the results could be a result of chance, given the size of the standard errors of the coefficients. The results leave open many important questions, however. For instance, being male and being African American are both significantly associated with specializing in violence in some instances but not in others. Additional research will be needed to determine whether this variation in estimates of substantively important relationships reflects chance differences across samples in a true relationship, a relationship that genuinely differs depending on age or setting, or the spurious appearance of a relationship resulting from a type I error.

CONCLUSIONS

We began by noting that criminologists and policy makers have great interest in the issue of specialization, but a series of methodological issues have impeded our ability to acquire useful information about whether and why specialization occurs. To address these methodological issues, we proposed a new statistical tool for assessing the level of specialization, determining its stability over time, and modeling its predictors. In this article, we defined specialization in violence as the tendency for individuals to engage in violent rather than nonviolent offenses, independent from their overall rate of offending and taking into account the population base rate of each type of offense. We illustrated our approach using three data sets.

SUBSTANTIVE IMPLICATIONS

Although findings from previous studies have been mixed, especially for juveniles, we obtained clear evidence of specialization. Our analyses of self-report offending found more variation in individual specialization in violence than could be expected based on chance, which contrasts with several other studies of arrest and conviction records (Capaldi and Patterson, 1996; Farrington, 1991; Piquero, 2000). Our results also reveal that, although the magnitude of variation in specialization may be less than the overall tendency to offend, it is still considerable. We observed these patterns in all three data sets, adding credence to our results. Thus, contrary to the National Research Council passage cited earlier, violent offenders are not merely frequent offenders. Our findings fit well with research on the broader topic of the generality of deviance, which reveals that both generality and specificity are important components of the reliable and stable variance of each type of deviance (Osgood et al., 1988).

Why did we find significant specialization in violence when several others have not? In some instances we had greater statistical power to detect specialization because of our considerably larger samples (Capaldi and Patterson, 1996; Farrington, 1991). Our use of self-report measures is likely to have contributed as well because other studies suggest this approach yields greater evidence of specialization than official records by better representing the offense repertoires of individuals (Lynam, Piquero, and Moffitt, 2004; Sullivan et al., 2006). We also believe that our strong evidence for specialization is a reflection of the greater sensitivity of our statistical approach, which results from its incorporation of all available information combined with appropriate modeling of overall offending and item base rates.

Several prominent researchers have lately rejected either specialization or the concomitant notion that distinct offender subtypes exist (Felson, 2006; Gottfredson and Hirschi, 1990; Sampson and Laub, 2003). According to Gottfredson and Hirschi, individual offenders may sometimes commit a disproportionate number of identical offenses, but this seeming pattern reflects erratic variations in opportunities rather than lasting individual traits or preferences. In this view, probability would lead offenders to occasionally specialize in something before going back to specializing in nothing at all.

For specialization to offer added scientific value, then, the specializations of individuals must be stable over time and must be systematically related to antecedent factors. Our results indicate that the tendency to specialize in violence is relatively consistent over time. Indeed, the connection between earlier and later specialization is of roughly the same magnitude as that between earlier and later overall offending. If specialization is relatively stable, then it is worthwhile to try to predict who will specialize. The ability of our new technique to accommodate independent variables is highly useful in this regard. Although we offered no specific hypotheses about predictors of specialization (and therefore we will not risk interpreting specific results), we nevertheless found several significant predictors of specialization, with a modest level of consistency across time and samples. Although we can thus effectively rule out specialization as being merely a function of random, short-term variations in opportunity, considerable room exists to improve our ability to predict this phenomenon.

Because specialization among individuals is reliable and has systematic correlates, additional research using our method could have important implications for theory. First, our findings support the potential value of theories that attribute specialization to something other than transitory, ephemeral factors, such as theories specifically addressing violence rather than crime in general (R. Felson, 2002; Tedeschi and Felson, 1994; Wolfgang and Ferracuti, 1967). Whether any specific theory of offender specialization is correct is, of course, another matter. Second, our limited ability to establish consistent correlates of specialization make clear that explicit and well-developed theory is essential if we are to advance research in this area. Theory would enable us to have greater confidence that our predictors of specialization are substantively important rather than a by-product of chance.

We believe that findings about correlates of specialization should prove especially valuable for developing and refining criminological theory. To illustrate, consider religiosity, which usually correlates with somewhat less crime (Baier and Wright, 2001). Our results showed, however, that when those who are religious do break the law, they are more likely than other offenders to engage in violence. Why would religiosity more strongly prevent one type of crime than another? This pattern could be an important clue for developing more nuanced theory that more fully and faithfully articulates the processes linking religion and crime, whether those processes involve social interactions (Tedeschi and Felson, 1994), differentiation in group norms (Akers, 1985), particular personality traits (Miller and Lynam, 2001), or situational factors that produce specific types of opportunity (Cohen and Felson, 1979; M. Felson, 2002).

METHODOLOGICAL IMPLICATIONS

The study of criminal specialization has proven difficult. Although criminologists have generated a variety of helpful tools for addressing the topic (Blumstein and Larson, 1969; Britt, 1996; Farrington, 1986, 1991; Mazerolle et al., 2000), progress has remained limited by numerous methodological challenges. The most sophisticated methods have addressed sequential specialization, but this approach is effectively limited to official data, ignores similarity among any offenses that are not temporally adjacent, and characterizes aggregate rather than individual specialization. The alternative is defining specialization through the variety or diversity of offending. Although researchers have applied this approach to self-report data and individual-level analysis, they have not disentangled specialization from overall offending or offense base rates, both of which are essential.

We have addressed these issues by casting individual specialization in violence in terms of an item response model within a multilevel analysis framework. Our approach makes use of information about similarity among all offenses, regardless of offense order. We define specialization in violence as a latent variable in order to conceptually and empirically distinguish specialization from the overall propensity to offend, while also taking into account the dependence of precision on overall offense rate. Our analytic framework also integrates all these strengths into models of the relationship of specialization to explanatory variables. We believe that this approach is an important advance for the study of specialization.

Our approach has its limits as well, which means that it should not and will not be the sole preferred method for future research on specialization. Our model is tailored to data sets with multiple items concerning two or more types of offenses. Self-report inventories provide such information, but official records of offending are likely too sparse for this approach. Also, our approach addresses specialization in a particular category of offense, rather than overall specialization across all categories, and both forms of specialization have been important in this research literature. Finally, our method implicitly assumes that each offense that a respondent reports reflects a different event, which may or may not be the case in most studies. Future research should test our results using measures specifically designed to assure this is true.

Although we focus on specialization in violent versus nonviolent crime, our statistical approach has broader utility. This model is applicable to any research question concerning two mutually exclusive categories of offenses, so it could be used to investigate other aspects of an offender's crime repertoire as well. For instance, some researchers have argued that white collar crime has different antecedents than other crimes, a point that other researchers dispute (Gottfredson and Hirschi, 1990). An application of our model distinguishing these two types of offenses would address this question, and the same approach applies to serious versus minor offenses or predatory versus victimless offenses. Indeed, by carefully coding the attributes of items, one could define multiple dimensions of specialization in a single analysis, either as independent dimensions (e.g., violent versus property and serious versus minor) or as a series of mutually exclusive offense categories (e.g., violence, theft, vandalism, and drug offenses).

Finally, our analytic framework is readily extended to address a broad range of research questions about criminal careers or offending over the life course by incorporating longitudinal analyses of a measure of self-reported offending. All that is required is respecifying our model as a three-level hierarchical model, with items at level 1, time or measurement occasions at level 2, and individuals at level 3. This model would allow analysts to relate both general offending and specialization in violence to time-varying explanatory variables at level 2 and to time-stable explanatory variables at level 3.

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D. Wayne Osgood is a professor in the Crime, Law, and Justice Program of the Department of Sociology at Pennsylvania State University. His research interests include peers and delinquency, individual-level application of routine activity theory, the generality of deviance, and a variety of topics in life span criminology and criminal careers.

Christopher J. Schreck is an assistant professor in the Department of Criminal Justice at the Rochester Institute of Technology. His publications are primarily about the etiology of crime victimization, with a particular focus on using insights from criminological theory to explain why victims and offenders are often so similar. He is a past editor of the *Journal of Crime and Justice*.

Appendix A. Descriptive Statistics and Item Parameters for the G.R.E.A.T. Evaluation Measure of Self-Reported Delinquency

	Grade 8			Grade 9		
	% Yes	γ_{i0}	SE	% Yes	γ_{i0}	SE
Violence						
Carried a hidden weapon	18%	–.06	.05	16%	–.20	.06
Hit someone	44%	1.09	.06	39%	.85	.06
Attacked someone with a weapon	7%	–.86	.05	7%	–.92	.06
Robbery	4%	–1.31	.05	3%	–1.44	.05
Gang fight	11%	–.51	.05	8%	–.76	.06
Nonviolence						
Avoided paying [Reference item]	20%	[–1.31]	.05	21%	[–1.29]	.05
Skipped classes without an excuse	23%	.17	.05	35%	.66	.06
Lied about age to get into some place	30%	.48	.05	29%	.40	.06
Damaged or destroyed property	27%	.37	.05	22%	.09	.06
Burglary	10%	–.63	.05	8%	–.86	.06
Car theft	5%	–1.19	.05	5%	–1.35	.06
Sold marijuana	7%	–.95	.05	9%	–.83	.06
n		1,738			1,519	

NOTE: Lower values of γ_{i0} reflect greater item seriousness or “difficulty”; see equations 1 and 4. γ is the HLM population average estimate, and SE is its robust standard.

Appendix B. Descriptive Statistics and Item Parameters for the Montreal Study Measure of Self-Reported Delinquency

	Age 12 Years			Age 17 Years		
	% Yes	γ_{i0}	SE	% Yes	γ_{i0}	SE
Violence						
Beaten up someone to force to do things						
[Reference item]	13%	[–1.76]	.06	11%	[–1.88]	.10
Gang/group fighting	24%	.62	.08	16%	.31	.09
Used a weapon in a fight	10%	–.30	.08	9%	–.19	.09
Fist fight	52%	1.85	.08	29%	1.05	.08
Carried a weapon	17%	.22	.08	27%	.91	.08
Beaten someone who did nothing to you	8%	–.44	.08			
Thrown objects at people	12%	–.09	.08			
Nonviolence						
Shoplifting	12%	–.09	.08	20%	.58	.10
Enter without paying (e.g., movie, concert)	13%	.00	.08	22%	.62	.10
Trespassed	26%	.73	.08	25%	.83	.10
Damaged things that didn't belong to you	13%	–.02	.08			
Stole school items worth more than $10				7%	–.42	.11
Stole a bicycle				11%	–.10	.11
Bought, sold, or possessed stolen property				22%	.62	.10
Burglary				11%	–.06	.11
Damaged part of a car				10%	–.19	.11
Damaged things at school				7%	–.36	.11
n		901			736	

NOTE: Lower values of γ_{i0} reflect greater item seriousness or "difficulty"; see equations 1 and 4. γ is the HLM population average estimate, and SE is its robust standard.

Appendix C. Descriptive Statistics and Item Parameters for the Monitoring the Future Measure of Self-Reported Delinquency

	Age 18 Years		
	% Yes	γ_{i0}	**SE**
Violence			
Group/gang fight [Reference item]	19%	[–1.32]	.02
Hit an instructor or supervisor	3%	–1.36	.02
Fight at school or work	14%	–.29	.02
Hurt someone badly	13%	–.41	.02
Robbery	4%	–1.28	.02
Nonviolence			
Shoplifting	28%	.39	.03
Car theft	6%	–1.10	.03
Stole car part	5%	–1.15	.03
Trespassed	24%	.22	.03
Damaged school property	13%	–.41	.03
Damaged work property	7%	–.98	.03
n		7,190	

NOTE: Lower values of γ_{i0} reflect greater item seriousness or "difficulty"; see equations 1 and 4. γ is the HLM population average estimate, and SE is its robust standard.