DO OFFENDERS SPECIALIZE? A MULTILEVEL IRT ANALYSIS OF OFFENDING PATTERNS IN ADOLESCENCE AND EARLY ADULTHOOD

A Dissertation

Presented to

The Faculty of the Department of Psychology

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctoral of Philosophy

By

Jessica Klement

August 2018

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ABSTRACT

Research examining specialization in violence, or whether certain offenders commit violent crimes at a higher rate relative to their individual rate of offending, has important implications for policy makers and scholars alike. Despite good evidence for predictors of violence, most of these prior analyses focus on the frequency of violence, which is confounded by overall rate of offending and does not distinguish factors uniquely related to violent versus nonviolent offenses. Osgood and Schreck (2007) introduced an item response theory (IRT) measurement approach that is nested within a multilevel model, which overcomes many of earlier methods' shortcomings. Several studies using this method have found evidence of specialization in violence and stability in measurement among adolescents, but longitudinal samples have been limited to five years or less; differences between local environments have yet to be examined within this framework.

The current study utilized a multilevel IRT method of analysis to (a) determine whether individuals differ systematically in their pattern to commit violent versus nonviolent offenses; (b) determine whether there is stability (i.e., correlation) in the measurement of specialization and overall offending across our two measurement points; (c) examine demographic covariates, neuropsychological factors, peer risk factors, and environmental criminogenic risk factors; and (d) examine differences in the pattern of relationships between explanatory variables with overall offending compared to specialization. Altogether, our results provided several points in support of the existence of specialization as a phenomenon that is measurable, separate from the individual rate of offending and population base rates, and endures over time.

Table of Contents

List of Tables

Do Offenders Specialize? A Multilevel IRT Analysis of Offending Patterns in Adolescence and Early Adulthood

The notion of identifying offenders based on their tendency to commit a particular type of crime dates back to the research of Cesare Lombroso in the late 1800s, who attempted to identify offenders based on individual physical and psychological features (Lombroso, 2006). Initially, the study of "specialization" in offending largely focused on the tendency for individuals to repeat specific types of offenses on successive criminal events (Wolfgang, Figlio, & Sellin, 1972). The definition of specialization has evolved along with advances in statistical methods, with more recent research examining the tendency for individuals to commit an offense type (e.g., violent offenses or nonviolent offenses) at a higher rate compared to both individual and population rates of offending (e.g., Farrington, Snyder, & Finnegan, 1988; Osgood & Schreck, 2007).

The question of whether specialization exists is of interest to scholars as many theories of crime involve typologies of offenders, which assume distinct subgroups of offenders that may vary in terms of patterns of offending and origin of their antisocial behavior. One of the most prominent typologies, Moffitt's developmental taxonomy of antisocial behavior, divides offenders into two types: adolescence-limited offenders and persistent antisocial offenders (Moffitt, 1993). Her theory suggests that adolescent-limited (AL) offenders account for the peak in offending during adolescence and tend to commit various types of non-violent offenses. Life-course persistent (LCP) offenders, on the other hand, are a qualitatively distinct group that demonstrates both diversity in the variety of crimes they commit throughout the lifespan and specialization (as we define it), with a greater propensity for serious and violent crimes. In other words, AL offenders tend to

specialize in non-violent offenses, and LCP offenders show versatility throughout their criminal careers with greater specialization in violent offenses. Other scholars have argued against the concept of specialization and unique etiologies for offense types. Gottfredson and Hirschi (1990) make this argument in their general theory of crime, which proposes that a unifying factor (i.e., lack of self control) explains all antisocial behavior. In their view, differences in offending simply reflect differences in self-control. Evidence of specialization would support theories of criminal behavior that make distinctions among offenders based on differences in offending patterns (e.g., Moffitt's developmental taxonomy), whereas evidence of versatility (lack of specialization) would support more general explanations of crime, such as Gottfredson and Hirschi's self-control theory of crime (1990).

Policy makers are especially interested in specialization due to the potential to target resources towards specific prevention and intervention efforts as well as inform the structure of justice processing and sanctions. For example, some states have laws that make waiver, or the transfer of juveniles to adult courts, mandatory within certain ages for certain offenses. These typically include violent offenses and certain types of property, weapon, and drug offenses (U.S. Department of Justice, 2011). For example, in the state of Vermont a child as young as 10 years can be transferred to the criminal court per judge discretion for certain person and property offenses. A child over 10 years can be waived from the juvenile court by judge discretion for any criminal offense in the state of Kansas. The supposed purpose of these transfer laws is to deter juveniles from committing more serious crimes. Many states also have a "once adult/always adult" law that requires criminal prosecution once a juvenile has been prosecuted in the past, regardless of the current offense. Recent estimates reveal about 4,000 juveniles are waived to adult criminal court each year (Furdella and

Puzzanchera, 2015). These policies assume that certain crimes predict more severe or chronic offending into adulthood. Furthermore, the courts generally rely on criminal history when determining risk and culpability in sentencing of current crimes. A recent study found that individuals who specialized in robbery or larceny (based on criminal histories) were less likely to have their current charge of a similar crime dismissed or reduced and more likely to be sentenced to jail or prison with a longer length of incarceration compared to those who specialized in the other six crime types (Yan, 2018).

So far, the evidence for specialization has been mixed. Inconsistencies in the research may be due to differences in the sample populations (e.g., community versus forensic samples), data source (e.g., official versus self-report), coding schemes for offense types, or length of time observed. Further complicating the state of the evidence, the advent of more advanced statistical methods has led to divergence in the operationalization of specialization. Due to these differences among methods in the conceptualization of specialization, comparison across studies is difficult. Some more recent studies attempted to address this issue by comparing multiple analytic approaches to studying specialization using a single data set (e.g., Boufard & Zedaker, 2016; Humphrey & Van Brunschot, 2017; Sullivan, McGlion, Ray, & Caudy, 2009). Generally, diversity in offending has been the norm in longitudinal research on the subject of specialization (Mazerolle et al., 2000; Piquero et al., 2007; Tzoumakis, Lussier, Le Blanc, & Davies, 2012). Sullivan et al. (2006) found evidence of specialization over shorter time periods (e.g., 25- to 36-months), but more diverse offending patterns emerged when the time periods are aggregated and a longer period of time is considered.

The earliest methods for studying specialization (e.g., transition matrices, Forward Specialization Coefficient) defined specialization as the tendency for offenders to repeat certain offenses on consecutive events or arrests (Wolfgang, Figlio, & Sellin, 1972; Farrington et al., 1988). Early research generally found a very small degree of specialization, if any, suggesting that versatility in criminal offending is the norm (e.g., Farrington et al., 1988). These earlier methods calculated aggregate level of specialization and relied on sequential, normally distributed data, a difficult assumption to make with criminal offending. They were also limited in their ability to test theoretical explanations for differences in offending patterns.

More recent methods tend to look at a particular period in time to assess the degree to which individuals vary in their tendency to commit certain types of offenses during that time period. Studies utilizing an item response theory measurement approach nested within a multilevel model have suggested a small degree of specialization among high-rate and low-rate offenders that is moderately stable over time (e.g., Osgood & Schreck, 2007; McGloin, Schreck, Stewart, & Ousey, 2011). Furthermore, advances in statistical methods overcome many of the drawbacks of previous methods, providing an individual-level measure of specialization that accounts for individual and population rates of offending, skewed data, and missing observations in longitudinal data. In particular, Osgood and Schreck (2007) introduced an item response theory measurement approach that is nested within a multilevel model, which overcomes many of the earlier methods' shortcomings and is more useful for testing theoretical conceptualizations of specialization. This approach defines specialization in terms of an inclination toward a particular type of offense compared to all other offenses that is independent from an individual's overall rate of offending and population base rates.

The ability to examine explanatory variables within the multilevel model framework has added value with its potential to guide theories and intervention.

In order to study potential specialization in violent versus nonviolent offending, the current study examined specialization among youth from the National Longitudinal Study of Adolescent Health as well as the stability of specialization across two time points: adolescence and early adulthood, spanning age 12 to 34 years of age. Following Osgood and Schreck (2007), our model uses an item response theory-based model nested within a hierarchical logistic regression model to determine the extent to which certain variables contribute to patterns in the types of offenses that individuals commit in adolescence and adulthood, as well as determine the stability in measurement over time. In sum, the current study sought to (a) determine whether individuals differ systematically in their pattern to commit violent versus nonviolent offenses (i.e., specialize); (b) determine whether there is stability (i.e., correlation) in the measurement of specialization and overall offending across our two measurement points; (c) examine demographic covariates, neuropsychological factors, peer risk factors, and environmental criminogenic risk factors that may relate to specialization; and (d) examine differences in the pattern of relationships between explanatory variables with overall offending compared to specialization.

Methodological Issues in Research on Criminal Specialization

Findings from previous research examining the extent of violence specialization have been inconsistent. Early research generally suggested that diversity or versatility in criminal offending was the norm. More recent and advanced methods have suggested a small degree of specialization among high-rate and low-rate offenders, alike (e.g., Osgood & Schreck, 2007). Some scholars suggest that inconsistencies in the research may be due to the use of

different sample populations (e.g., community versus forensic samples), coding schemes or operationalization of specialization. For example, research that has examined differences in measurement of violent offending strongly indicates a higher prevalence of violent offending based on self-report data compared to official reports of arrest or charges (Loeber, Farrington, & Waschbusch, 1998; Lynam, Piquero, & Moffitt, 2004; Piquero, 2000). In addition, the advent of different methods has led to divergence in the operationalization of specialization, leading to questions about whether different scholars are studying different dimensions of some concepts.

Earlier methods examined specialization with transition matrices, which are cross-tabulations in which rows indicate the type of offense committed at the first measurement point, and the columns indicate the type of offense committed at the second measurement point (Osgood & Schreck, 2007). Higher probabilities in the diagonal cells are indicative of specialization. Critics of this approach pointed out that the transition matrices would be more sensitive to detecting specialization in types of crimes that are more frequent, such as theft. Farrington et al. (1988) developed the forward specialization coefficient (FSC) as an improvement to transition matrices, which defined specialization as the tendency to repeat a specific offense type on a scale of 0 to 1. The FSC measured the specialization (consistency in this case) for each offense type and its aggregate level across offenses. The utility of these methods has been questioned due to the reliance on sequential data and assumptions of normal distribution (Britt, 1996). In addition, the FSC method assesses the average level of specialization for the sample but not the degree of specialization for individuals, and analyses of explanatory variables would require splitting the sample and running separate analyses for each variable.

The diversity index was the first method to consider the full range of crimes a person committed rather than sequence of two offenses. The diversity index computes the expected proportions of violent offenses based on the binomial distribution of violent and nonviolent offenses and theoretical percentages (see Piquero et al., 1999). Specialization, in this case, was defined as a lack of variety in the types of crimes committed. Because the diversity index is an individual-level measure, it also allows examination of explanatory variables in regression analyses. However, the maximum value of the diversity index varies according to the coding scheme (e.g., number and type of offending categories), so comparisons across samples are limited. The diversity index cannot provide insight into the types of crime that offenders specialize (e.g., violent offenses), and does not account for base rates in the population. In this way, the diversity index can provide information on absolute diversity, but not into the tendency to specialize in a particular offense type relative to the general population.

The latent class analysis (LCA) approach, typically used to examine offense trajectories, has more recently been applied to specialization in order to classify offenders. Similar to factor analysis, this approach assumes that a latent variable, with a certain number of mutually exclusive categories, explains the pattern of offending in the population of interest. The few specialization studies that have used this approach have demonstrated mixed results (e.g., Britt, 1996; Francis et al., 2004; McGloin et al., 2009; Soothill et al., 2002). Some scholars note that it is limited by confounding between offense frequency and specialization since the classes may be derived from both differences in incidence and type in cases where a count of number of offenses is used (Sullivan et al., 2009). In regards to specialization, LCA does not determine true “types.”

Most recently, Osgood and Schreck (2007) proposed a method for examining violence specialization, which is based on an item response theory measurement approach that is nested within a multilevel model. This method conceptualizes violence specialization in terms of an inclination toward violent offenses compared to nonviolent offenses that is independent from their overall rate of offending. The first level of the multilevel model uses a one-parameter (i.e., Rasch) item response theory model to determine the presence of specialization and, in the case of multiple time points, stability of specialization. The IRT model estimates the latent variables reflecting the tendency towards specialization and propensity for overall offending while controlling for sample base rates for each offense. Level two models investigate the relationship of various explanatory variables to specialization and overall offending as estimated at level one. The model and equations are described in greater detail in the methods.

The handful of studies that have implemented the multilevel IRT method proposed by Osgood and Schreck suggest some, but not strong, degree of violence specialization that is stable over time. Osgood and Schreck (2007) analyzed data from subjects from Monitoring the Future, Montreal Study, and Gang Resistance Education and Training (GREAT) samples using their multilevel IRT method. Results demonstrated significant specialization in violent crimes, which was not limited to high-rate offenders as some low-rate offenders also demonstrated a tendency towards violent crimes. The specialization measure demonstrated significant stability over time across the two data sets that measured self-reported delinquency longitudinally in adolescence.

Sullivan, McGion, Ray, and Caudy (2009) compared the degree specialization suggested by four different data analysis methods using a single dataset of 1,308 incarcerated

juvenile offenders in California. Criminal offending was obtained via official reports of crime from ages 18 to 21. Specialization was examined using (1) the forward specialization coefficient, (2) diversity index, (3) latent class analysis, and (4) a multilevel IRT model (as described by Osgood and Schreck, 2007). Though these methods did not exclusively test for violence specialization, results from all four methods revealed some, but not strong, degree of offending specialization. They concluded that the IRT method may provide the clearest evidence of specialization and best test for theory-based research questions. However, Sullivan et al. warn that specialization, in this case, is relative and not pure or absolute in terms of behavior. For example, someone with a tendency towards non-violent offenses may still commit a violent offense but the frequency will be low relative to the base rate of violent offending.

McGloin, Schreck, Stewart, and Ousey (2011) utilized Osgood and Schreck's model to examine specialization in violence and its association with values and beliefs favorable toward violence as suggested by the subculture of violence theoretical framework. Data was drawn from the Rural Substance Abuse and Violence Project (RSVP), a prospective four-wave panel study of adolescents living in Kentucky between 2001 and 2004. Results suggested significant degree of specialization in the sample across all four waves. Specialization exhibited some degree of stability, with violent offenders at Wave I often demonstrating a tendency for violent offenses at Wave II, II, and IV. Contrary to their hypothesis, however, the subculture of violence predicted overall offending but not a tendency to favor violent crime. Overall, this study provided support for specialization and the utility of the Osgood and Schreck model for testing theories of criminal offending.

Osgood and Schreck's multilevel IRT model has several advantages compared to previously described methods. First, this method can identify a particular type of specialization, such as violence, as opposed to overall specialization. It does not rely on sequential data and can accommodate unequal time points, which makes it suitable for self-report data and official data alike. By isolating specialization from overall rates of offending, this method overcomes the confounding associated with previous methods. Finally, specialization is defined at the individual level rather than relying on aggregates, which allows for regression modeling of explanatory variables. This feature makes this method especially suited to testing theory-based research questions and makes use of all available data instead of restricting the analysis to respondents who have committed a minimum number of offenses, as was done in earlier methods.

The Current Study

The current study will examine specialization, or whether individuals differ systematically, in their tendency to commit violent versus nonviolent offenses across two measurement points, adolescence and early adulthood, spanning an average of 13 years. To our knowledge, the few studies that have implemented this method have been limited to adolescence and have covered measurement periods of five years or less. We aimed to expand on existing research by testing the stability of specialization in violent versus nonviolent offenses over a period of approximately 13 years, covering the periods of adolescence and early adulthood. We also added to existing research by including a third level of analysis to examine the contribution of differences between local environments, such as schools, to individual differences in the tendency to commit violent versus nonviolent offenses.

The aims of the present study were to (a) determine whether individuals differ systematically in their pattern to commit violent versus nonviolent offenses (i.e., specialize); (b) determine whether there is stability (i.e., correlation) in the measurement of specialization and overall offending across our two measurement points; (c) examine demographic covariates, neuropsychological factors, peer risk factors, and environmental criminogenic risk factors that may relate to specialization; and (d) examine differences in the pattern of relationships between explanatory variables and individual differences in overall offending compared to specialization. Significant specialization in violent versus nonviolent offenses was expected among respondents at both measurement points: Wave 1 (adolescents 12 to 21 years) and Wave 4 (young adults 24 to 34 years; hypothesis 1). In other words, we expected that offenders would systematically differ in their tendency to endorse violent versus nonviolent offenses. We further expected that the measurements of specialization and overall offending would demonstrate at least moderate stability across adolescence and early adulthood (Hypothesis 2). We defined stability as the correlation of our measure with itself over time. For example, we predicted that specialization measured at Wave 1 would be moderately correlated with specialization measured at Wave 4.

We were also interested in identifying variables that might explain individuals' tendency to prefer violent or nonviolent offenses. We expected peer drug use, individual and community/school indicators of low socioeconomic status to be negatively associated with our specialization measure (Hypothesis 3). In other words, we expected that they would associate with a greater tendency to commit nonviolent over violent offenses. Delinquent peers are one of the strongest and most consistent predictors of delinquency and youth violence (Herrenkohl et al., 2003; Loeber & Farrington, 1998); however, few researchers

have examined the unique relationships between nonviolent and violent offending among peers with adolescent specialization. McGloin et al. 2011 found a significant relationship between peer specialization in violent versus nonviolent offending and adolescents' tendency to specialize. While not a direct measure of nonviolent peer delinquency, we suspected that peer drug use would be indicative of modeling and reinforcement of deviant peer attitudes. We also expected that individual and community/school indicators of low socioeconomic status would be associated with a greater tendency to commit nonviolent offenses with the rationale that individuals with greater socioeconomic advantage would have less incentive to commit nonviolent offenses, which in our study primarily constituted theft and other illegal means of acquiring monetary goods. These socioeconomic indicators include parent educational attainment and parent-reported public assistance at Wave 1, and respondent educational attainment and total household income at Wave 4. The proportion of persons below the poverty level per the Census Bureau's American Community Survey (ACS) was also included for Wave 1 and Wave 4 estimates. Unemployment rate was included for Wave 4 estimates.

In regards to variables that might be uniquely associated with a greater tendency towards violent offenses, we expected that neuropsychological factors and violent crime arrest rates in the community would be associated with a greater tendency to commit violent over nonviolent offenses among individuals (Hypothesis 4). The role of neuropsychological factors in violent offending is not a new concept (see Bryant, Scott, Tori, & Golden, 1984). There is strong evidence for the relationship between neuropsychological challenges and level of violent offending (Guo, Roettger, & Cai, 2008; Moffitt & Caspi, 2001; McNulty, Bellair, & Watts, 2012), but scholars suggest a number of confounds, such as low SES,

school environment, and school achievement. We examined individual factors suggestive of neuropsychological deficits, including parent-reported learning disability, low birth weight, and verbal ability (measured by the Peabody Picture Vocabulary Test) while controlling for grade point average and socioeconomic status. We differentiated between levels of violent crime and nonviolent crime in the community by controlling for community level estimates of property crime arrest rates.

We also examined the relationship between covariates with overall offending for the purpose of identifying differences in their pattern of relationships to overall propensity to offend compared to specialization. Because the primary aim of our study was to examine specialization and our covariates were selected for this purpose, we included no a-priori hypotheses for their relationship to overall offending. Generally, we expected that the pattern of relationships between covariates and overall offending would differ from the pattern for specialization (Hypothesis 5).

Method

Data and Sample

Add Health study design. Add Health is a school-based longitudinal study of adolescents in 7th to 12th grade in the United States (www.cpc.unc.edu/addhealth). High schools were randomly selected from a sampling frame stratified by size, region, urbanicity, and percentage white. Selected high schools were matched with their primary feeder school that included 7th grade. There are a total of 132 schools in the study. Of the eligible students in grades 7-12, 90,118 respondents completed an in-school paper-and-pencil survey during the 1994-1995 school year. A subsample (Wave 1; ages 12-21; n=20,745), stratified by grade and gender, was selected for a 90-minute computer-assisted in-home interview between April

and December 1995. Sensitive questions were delivered through earphones and adolescents entered their responses directly onto a laptop computer, a method shown to maximize reporting among adolescents (Turner, Rogers, et al., 1998). All of the Wave 1 participants, excluding the 12th graders, were invited to complete a follow-up survey between April and September 1996 (Wave 2; n=14,738). All Wave 1 participants, including 12th graders, who could be located and interviewed, participated in Wave 3 interviews (Wave 3; ages 18-26; n=15,170) between 2001 and 2002. Ninety two percent of Wave 1 participants were located for a fourth in-home interview and biological specimen collection and 80% participated between 2008 and 2009 (Wave 4; ages 24-34; n=15,701).

Study sample and eligibility criteria. For the current study, the sample included participants from the restricted dataset who completed the in-home interviews at Wave 1 and Wave 4.

Measures

Dependent variables. Our outcome measures were based on self-report items measuring participants' involvement in non-violent and violent offenses in the past 12 months.

Nonviolent offending. During Wave 1, participants completed eleven items asking their involvement in the following over the past 12 months: theft, burglary, destruction of property, graffiti, truancy, running away, sex work, selling drugs, marijuana use, cocaine use, and other drug use. Wave 4 included nine items measuring participants' involvement in the following: check forgery, sex work, burglary, theft, buying/selling stolen goods, using a stolen credit card, destruction of property, selling drugs, and marijuana use. Responses were dichotomous, with endorsement coded as "1" and otherwise "0."

Violent offending. Wave 1 and 4 included six items measuring participants' involvement in the following violent acts: battery (i.e., seriously injure someone), group fight, serious fight, armed robbery, threatened someone with knife/gun, and shoot/stab someone. Responses were dichotomous, with endorsement coded as "1" and otherwise "0."

Demographic variables. Demographic characteristics, such as gender, race/ethnicity, age, and socioeconomic status (SES), as measured by parent-reported public assistance and parent education were included due to evidence of their confounding effects **(**Resnick et al., 1997). In addition, we included a measure of primary language spoken in the home due to significantly lower measure of verbal ability among individuals who live in a non English-speaking home compared to those from an English-speaking home ($t=-29$, $p<0.001$).

Gender. Participants reported their gender at Wave 1 of the in-home interview. Responses included male (0) or female (1).

Race/ethnicity. Race and ethnicity were assessed during Wave 1 of the in-home interview. The following responses were transformed into dummy variables: *White* (non-Hispanic), *Hispanic or Latino, Black or African American, American Indian or Native American, Asian or Pacific Islander, or Other.*

Public assistance. During the parent in-home questionnaire at Wave 1, parents were asked whether they or any member of their household received social assistance as measured by five dichotomous items: (a) Social Security or Railroad Retirement, (b) Supplemental Security Income, (c) Aid to Families with Dependent Children, (d) food stamps, (e) unemployment or workers compensations, or (f) a housing subsidy or public housing. Responses were be coded as *yes* (1) or *no* (0). Wickrama et al. (2010) found this measure to be internally consistent (KR-20=0.85).

Parent education. Parents' highest level of education was measured using two items from the parent in-home questionnaire. The first question asked parents to identify their highest level of education, while the second question asked parents to identify their spouse's highest level of education. Responses included *never went to school* (6), *8th grade or less* (5), *more than 8th grade, but did not graduate from high school* (4), high school graduate or equivalent (3), some college (2), four year college degree (1), or *professional training beyond a 4-year college or university* (0). This item is reverse coded with lower value indicating higher educational attainment. The lowest response of the two items was retained to reflect the highest level of education among two-parent families, or the educational attainment among single-parent families.

Household income. Participants reported their total household income before taxes and deductions at Wave 4. Responses included less than $5,000 (1), $5,000 to $9,999 (2), $10,000 to $14,999 (3), $15,000 to $19,999 (4), $20,000 to $24,999 (5), $25,000 to $29,999 (6), $30,000 to $39,999 (7), $40,000 to $49,999 (8), $50,000 to $74,999 (9), $75,000 to $99,999 (10), $100,000 to $149,000 (11), or $150,000 or more.

Educational attainment. Participants reported their highest level of education to date at Wave 4. Responses included 8th grade or less (1), some high school (2), high school diploma (3), some vocational or technical training beyond high school (4), completed vocational or technical certificate after high school (5), some college (6), complete bachelor's degree (7), some graduate school (8), completed a master's degree (9), some graduate training beyond a master's degree (10), or completed a doctoral degree (11).

English not spoken in home. Participants were asked at Wave 1 what language was primarily spoken in their home. Responses were coded as English (0) or Otherwise (1).

Neuropsychological factors.

Low birth weight. Birth weight was measured during the in-home parent questionnaire at Wave 1. Participants' parents reported how much he or she (the participant) weighed at birth. This variable is dichotomous, with a cut-point of less than five pounds and eight ounces coded as "1," following the medical definition of low birth weight. Otherwise, responses were coded as "0."

Learning disability. This variable is based on a single-item measure from the Wave 1 in-home parent questionnaire. Participants' parents were asked: *Does (he/ she) have a specific learning disability, such as difficulties with attention, dyslexia, or some other reading, spelling, writing, or math disability?* Response options were dichotomous (yes=1, no=0).

Verbal ability. The PVT, a slightly abbreviated version of the Peabody Picture Vocabulary Test, was given at Wave 1. It is generally regarded as a verbal ability test among researchers (Guo et al., 2008). Responses are continuous but were coded to distinguish those individuals who have at least average verbal intelligence (90 or greater)=0, low average verbal intelligence (80 to 89)=1, borderline impaired verbal intelligence (70 to 79)=2, or impaired verbal intelligence (less than 70)=3. Due to potential confounding effects, we controlled for whether English is spoken in participants' home, described above.

Grade Point Average (GPA). The mean of four items, which measure self-reported grades in English, Math, History at Waves 1, determines participants' GPA. Responses included A (4), B (3), C (2), or D or less (1). Cronbach's alpha for this scale was 0.71.

Peer risk factors.

Peer marijuana use. This measure assesses the adolescent's level of association with peers who use marijuana. The measure equals the sum of three items asked during Wave 1, which measured how many of the participants' three best friends use marijuana at least once a month.

Peer alcohol use. This measure assesses the adolescent's level of association with peers who use alcohol. The measure equals the sum of three items asked during Wave 1, which measured how many of the participants' three best friends use alcohol at least once a month.

Criminogenic environmental risk factors.

Property crime arrest rates. The Uniform Crime Report (UCR) is periodic compilation of reported crimes nationwide; it contains county-level counts of arrests for property offenses. Total arrests for property crimes per 100,000 were estimated for the reporting county at Wave 1 and Wave 4. Rate of property crime was aggregated at the school level to include in the third level of our mixed hierarchical linear model for Wave 1. While some individuals may live in a county different from their school, we estimate that the proportion of these individuals is very small. Pearson bivariate correlation between the original and aggregated variable is 0.98, $p<0.001$. Because area-level mapping was not available for analyses at the time of these analyses, we incorporated community-level indicators of property arrests at the individual level of analysis for Wave 4.

Violent crime arrest rates. Arrests for violent crimes, from assaults to murders, per 100,000 were estimated from the UCR for the reporting county at Wave 1 and Wave 4. Similar to property crime, the rate of violent crime was aggregated at the school level for Wave 1. Pearson bivariate correlation between the original variable and the aggregated

variable is 0.99, $p<0.001$. We incorporated community-level indicators of violent arrests at the individual level of analysis for Wave 4 due to unavailable area-level mapping.

Concentrated Poverty. The proportion of the population living below the poverty level in the past 12 months for the reporting area was derived from the Census Bureau's American Community Survey (ACS) 5-year estimates aggregated from 2005 to 2009. The accumulated five year sample should include approximately 1 in 8 households. Proportion of persons living in poverty was aggregated at the school level for Wave 1. Pearson bivariate correlation between the original variable and the aggregated variable is 0.8, $p<0.001$. This variable was incorporated at the individual level of analysis for Wave 4 due to unavailable area-level mapping for individuals. Estimates correspond to the census tract in which respondents were living at the corresponding time of measurement. A census tract is a small statistical subdivision originally designed to be homogenous with regard to population characteristics, economic status, and living conditions (Census Bureau, 2009).

Unemployment rate. The total proportion of unemployed persons 16 years and older were acquired from tract-level measures reported by the U.S. Census Bureau's ACS.

Data Analysis Plan

Preliminary Analyses. Descriptive statistics for all study variables were estimated in SPSS Statistical Software Version 25.0 (IBM Corp., 2017). We estimated the rate of endorsement for all offenses. The normality for all continuous covariates was tested using skewness and kurtosis values, as well as visual inspection of Q-Q plots. Bivariate correlations were used to examine the interrelations among continuous study covariates, as well as their relation to ordinal and ratio study covariates.

Hierarchical Linear Modeling. We have followed Osgood and Schreck (2007) and Raudenbush, Johnson, and Sampson (2003) in using an item response model implemented within a multilevel, also known as hierarchical linear modeling (HLM), framework. Combining IRT and HLM allows individual offense item responses (level 1) to be nested within individual subjects (level 2), who are then nested within schools (level 3). Our model for Wave 1 is equivalent to a three-level hierarchical logistic regression model with two latent variables (e.g., overall offending and specialization) defined as random effects. The HLM approach provides a framework for incorporating covariates to account for variation between-persons (at level 2) and variation between-schools (at level 3). In addition, estimating latent variables as random effects by maximum likelihood allows the incorporation of data missing at random and retains all respondent information; this departs from the traditional estimation of item severities and person propensities as fixed effects in the classical Rasch model (Raudenbush et al., 2003). Per Osgood and Schreck (2007), assumptions for our nested model were similar to the assumptions for IRT and multilevel regression models alone. The measurement model assumes local independence, equal item discrimination, and unidimensionality (Raudenbush et al., 2003). Our random effects model (i.e., our HLM model) assumed a multivariate normal distribution of residuals (Raudenbush & Bryk, 2002).

The models differ slightly at each wave due to differences among items and nesting structure. While our model at Wave 1 is a three-level hierarchical logistic regression model, our model at Wave 4 is a two-level hierarchical logistic regression model with item responses nested within individuals because grouping structure was unavailable at the time of these

analyses. We incorporated available community-level indicators of crime and poverty at the second level of our HLM model at Wave 4 since area-level mapping was unavailable.

The measurement model. Following Osgood and Schreck (2007), our level 1 model (equation 1) defines two latent variables as random effects, one for overall offending (β_{0j}) and one for violence specialization (β_{1j}). When a respondent endorses having committed an offense item, Yij=1, otherwise $Yij = 0$. The nonlinear link function related the probabilities of possible responses for each item to the latent variables that were estimated. The logistic link function assumes a Bernoulli probability distribution. The log odds (or probability) that an individual will endorse an offense item depends on three factors: the person's overall level of offending, item base rates, and specialization. The level 1 regression equation is:

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

Our measurement model falls under the class of IRT models known as a Rasch model. It is considered a one-parameter model because it estimates one parameter (β_{ij}) for each item (i.e., the item difficulty parameter) to allow for differences in the base rates across items. Item parameters are fixed across individuals and are assumed equal to population estimates (see equation 4 below). The item parameters for our measurement model represented differences in base rates among the items in the log odds metric, avoiding confounding between our specialization measure and base-rate differences across items.

The intercept of equation 1 (β_{0j}), defines the latent measure for overall offending and therefore is constant across items. The residual term in its level 2 equation (Equation 2) indicates that it varies randomly across individuals. The magnitude of our variance component (i.e., variance of the residual term) indicates the extent to which individuals differ in overall offending.

The third factor, specialization, is estimated by our random variable (β_{1j}). The variable "Spec" was coded as a contrast variable that represents the balance in violent to nonviolent offenses for each person. For violent items, Spec equals the proportion of responses that concern nonviolent offenses. For nonviolent items, Spec equals minus the proportion of responses that concern violent offenses. In this way, the specialization index takes on positive scores for violent offense items and negative scores for nonviolent offense items, averaging to zero within each person. Ensuring that there was no variance across individuals avoided any confound between specialization and the overall rate of offending. The correlation coefficient for Spec estimates the difference in the log of the expected event-rate for violent offenses to the log of the expected event-rate for nonviolent offenses.

The statistical significance of our variance components (τ) (for each wave of data) told us whether the difference among individuals on our latent measures is greater than would be expected by chance (Hypothesis 1).

Relating our measures to explanatory variables. The level 2 models can estimate the association between extraneous predictors with our latent measures for specialization and overall offending. The level 2 regression equations are:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} X_{1j} + \gamma_{02} X_{2j} + \ldots + u_{0j} \quad (2)$$

$$\beta_{1j} = \gamma_{11} X_{1j} + \gamma_{12} X_{2j} + \ldots + u_{1j} \quad (3)$$

$$\beta_{ij} = \gamma_{i0} \quad (4)$$

Equation 2 estimated regression coefficient (Y_{01}) for the association between the explanatory variable (X_1) and the latent score (β_{0j}) of individual *j* for overall offending. The regression coefficient indicated the increase in log odds of committing each offense for each one-unit increase in the explanatory variable. A significant regression coefficient for an

explanatory variable indicated a significant association with the propensity for overall offending (Hypothesis 5).

Equation 3 estimated the regression coefficient (Y_{11}) for the association between the explanatory variable (X_1) and the latent score (β_{1j}) of individual *j* for specialization. More specifically, the coefficients associated with the explanatory variables estimated the change in logged incident rate ratio of violent-to-nonviolent offense scores for each unit increase in the explanatory variable. A positive regression coefficient (Y_{11}) indicated that higher scores on the explanatory variable (X_1) coincided with a tendency for violent over nonviolent offenses. Conversely, a negative regression coefficient (Y_{11}) indicated that higher scores on the explanatory variable (X_1) coincided with a tendency for nonviolent over violent offenses. In this way, peer drug use, individual and area level indicators of socioeconomic status should have demonstrated a negative regression coefficient for the association with specialization (Hypothesis 3); while we expected that low birth weight, learning disability, verbal ability, and area level of violent crime would demonstrate a positive regression coefficient for specialization (Hypothesis 4).

The stability of measures of overall offending and specialization can be estimated with multiple waves at level 1 (Hypothesis 2). We defined stability as the correlation of the latent specialization measure with itself over time. We did this by stacking our data and creating a dummy variable "Time" that equals "0" if the response is from Wave 1 and "1" if the response is from Wave 4. We expanded our HLM model to include items from both waves and added our dummy variable "Time." The intercept of our new model was equal to the overall offending measure for Wave 1, and the coefficient for Time was equal to the overall offending measure for Wave 4. HLM estimates the covariance between our (now

four) random effects. The covariance between the covariance components for Time and intercept provided an estimate of stability for overall offending. The covariance between the random effects of specialization at Wave 1 (Spec0) and specialization at Wave 4 (Spec1) provided an estimate for the stability of our specialization measure. Including the items from both waves in the model placed the latent measures on the same scale even if some of the items are not measured at both times.

Hierarchical logistic linear regression analyses were carried out using HLM 7.01 (Raudenbush, Bryk, Cheong, Fai, Congdon, & du Toit, 2013), a commercially available software program. Backward elimination was utilized, removing insignificant covariates in steps to identify a final model with the best fit per the deviance statistic. To account for unequal sampling probabilities, all models were scaled using the most appropriate weight recommended by Add Health's User's Guide for longitudinal analysis: the sampling weight calculated for participants interviewed at Wave 1 and 4 for population average models. Stata Statistical Software was used to check assumptions of our measurement model (StataCorp., 2017). First, we conducted a factor analysis using a tetrachoric correlation matrix in Stata to estimate each item's loading onto a single factor. Then we compared results of a one-parameter model to a two-parameter model to check our assumption of equal item discrimination. Finally, we calculated the bivariate correlations of our item residuals to check for violations of local independence. We used SPSS to code variables and prepare data for analyses in Stata and HLM (IBM Corp., 2017). Standardized residuals of our hierarchical logistic linear regression models were exported from HLM to SPSS, and skewness, kurtosis, and visual inspection of histograms and Q-Q plots were examined to check for violations of multivariate normality.

Results

Descriptive Statistics

The means and standard deviations were calculated for all covariates prior to centering continuous variables (Table 1). In regards to the racial and ethnic identity of the sample, Non Latino Whites accounted for 47% of the sample, followed by 20% African American or Black, 15% Latino or Hispanic, 7% Asian or Pacific Islander, 3% Native American or American Indian, and approximately 8% indicating other race/ethnicity. The average age at Wave 1 was 15 years of age, while the mean age was 28.5 at Wave 4. Males accounted for 50.5% of the sample at Wave 1 and 53% of the sample at Wave 4.

Compared to population estimates, the Add Health sample has similar rates of low birth weight, with 6.2% endorsement in our sample compared to estimated 8% in the U.S. population in 1980 (the average year of birth for the sample; Martin et al., 2002). The proportion of average or higher verbal ability in our sample (76%) is also comparable to population estimates at 75% (Bureau of Census, 1995). An estimated 13% of all students three to 21 years old were served under Individuals with disabilities Education Act in 2014 to 2015 (USDOE NCES, 2016). These estimates include all disabilities, such as developmental delay, physical disabilities, or specific learning disabilities. Endorsement of learning disability among parents in the Add Health sample at Wave 1 is approximately 13%. Parent reported learning disability should not be interpreted in the clinical sense but is more likely an indication of "learning difficulties" in school.

In regards to educational attainment, approximately 76% of respondents at Wave 1 had a parent with a high school diploma or higher. About 92% of respondents at Wave 4 reported a high school diploma or higher, and 65% reported some college education. At

Wave 4, the average reported household income was between 40,000 and 49,000 dollars. Adjusted for inflation rates since 2006, this would equate to the purchasing power of about 49, 700 dollars in 2018 (US Bureau of Labor Statistics).

Rates of endorsement and missing data for offending items were examined. Estimates of the violent and nonviolent offending item frequencies revealed large percentage of missing responses for items related to use of drugs at both Wave 1 (e.g., Marijuana use, Cocaine Use, Other Drug Use) and Wave 4 (e.g., Marijuana use). Over 70% of respondents did not answer these items. In addition, the item that queries respondents' involvements in sex work at Wave 4 was missing 15% of responses. Ninety five percent of respondents did not answer the item pertaining to seriously injuring someone in a fight. These items were removed from our IRT and HLM outcome measures. Remaining items were missing less than 10 percent of responses, which is generally considered acceptable (Bennett, 2001). Rates of endorsement for the remaining items are listed in Table 2.

Bivariate Correlations

We examined Q-Q plots and skewness and kurtosis statistics for all continuous covariates, which included area-level covariates and age. Violent crime arrest rate, property crime arrest rate, concentration of poverty followed a non-normal distribution at both waves. Age appeared to follow a normal distribution at both waves. Therefore, we estimated Spearman correlations, a nonparametric correlation, for all continuous area-level covariates and their bivariate correlations with ordinal and interval study covariates. We report the results for Wave 1 and 4 separately below.

Wave 1 Spearman Correlations. The results of Spearman correlations revealed a significant correlation between family public assistance and parent education (reverse-

coded), such that higher parent education is associated with lower levels of public assistance (rho=0.26, p<0.001). Both parent measures of socioeconomic status were also significantly related to respondent GPA, with higher GPA associated with less public assistance (rho=-0.16, p<0.001) and higher levels of parent education (rho=-0.25, p.<0.001). Older respondents tended to report higher levels of peer alcohol use (rho=0.28, p<0.001) and peer marijuana use (rho=0.17, p<0.001). Similarly, respondents reporting a higher GPA also reported lower levels of peer alcohol use (rho=-0.16, p<0.001) and peer marijuana use (rho=-0.21, p<0.001).

In regards to area-level covariates, on average, violent crime arrest rate was also associated with higher concentration of poverty (rho=0.1, p<0.001). Parents who lived in areas with higher concentration of poverty reported higher levels of public assistance (rho=0.28, p<0.001) and lower levels of educational attainment (0.28, p<0.001). Altogether, these results support the phenomenon that disadvantage tends to be concentrated within clusters, which has notable effects on crime (e.g., Sampson, Raudenbush, and Earls, 1999).

Wave 4 Spearman Correlations. Unsurprisingly, respondents with a higher educational attainment lived in an area with lower concentration of poverty (rho=-0.20, p<0.001) and unemployment rate (rho=-0.19, p<.001) on average. Higher educational attainment was significantly related to a lower property crime arrest rate, but the correlation was very small (rho=-0.03, p<0.001). Similarly, respondents who reported a higher household income, on average, lived in an area with lower property crime arrest rates (rho=-0.54, p<0.001) and unemployment rates (rho=-0.22, p<0.001). Household income and education level were unrelated to violent crime arrest rates. Concentration of poverty within census tracts was highly correlated with total unemployment rate (rho=0.54, p<0.001).

Checking Model Assumptions

Unidimensionality. Item response models assume that individual differences in responding to a scale are due to a person's location on a single latent trait, which is referred to as "theta." Local independence and unidimensionality are related in that the relationship between items should be explained by the items' relationship to the latent trait. We conducted a factor analysis using a tetrachoric correlation matrix in Stata to estimate each item's loading onto a single factor. The tetrachoric correlation is used to estimate the correlation between two dichotomous variables that are assumed to come from normally distributed and continuous latent variables. Results are shown in Table 3. At Wave 1, sex work, truancy, running away, and selling drugs demonstrated poor factor loading. At Wave 4, check forgery and using a stolen credit card demonstrated poor factor loading.

Equal item discrimination. The one-parameter "Rasch" model assumes that all items are equally discriminating (Raudenbush et al., 2003). Put another way, our model assumed that no substantial differences existed across items in their relation to the latent variables that define overall offending and specialization. We checked this assumption by comparing results based on one-parameter and two-parameter models. We estimated a Rasch model using a computer program named STATA (StataCorp., 2017) and compared the results with those based on a two-parameter model using STATA. The scale for Wave 1 included 11 items (discussed in previous section). There were 11 items that met our assumption of unidimensionality for Wave 4. Under the Rasch model, item difficulty estimates can be interpreted as item severities (Raudenbush et al., 2003). More difficult items will have lower rates of endorsement.

Comparison of one-parameter and two-parameter latent models revealed differences in item discrimination for our outcome measure at Wave 1 and Wave 4. Inspection of item discrimination parameters and item characteristic curves in the two-parameter models showed that items are not equally discriminating. At Wave 1, shot/stabbed someone had the largest slope and greatest standard error estimates for both item difficulty and discrimination. Similarly, Wave 4 showed a single item, burglary, with larger than average slope and standard error. While items that are highly discriminating are typically considered desirable in two-parameter item response models, an item with higher than average correlation to the total score could indicate redundancy, or that the item is dependent on other items. We, therefore, removed these items from the models and estimated one-parameter and two-parameter models with the remaining 10 items for Wave 1 and remaining 9 items for Wave 4. Results for Wave 1 are shown in Table 4, and the results for Wave 4 are shown in Table 5. Although the model fit appears to improve with removal of these items, estimates of the Bayesian information criterion (BIC) suggest that the two-parameter model is a slightly better fit for the items. The violent items appeared to have steeper slopes (i.e., greater discrimination) compared to the nonviolent items, with the exclusion of burglary at Wave 4. As noted by Osgood and Schreck (2007: 287-8) this is consistent with the basic assumptions of their approach, which estimates latent variables for both overall offending and specialization in violence. We estimated correlations between item residuals (described below) to ensure that covariation between items do not violate the assumption of local independence.

Local independence. Local independence is related to unidimensionality and, as stated above, the assumption of equal item discrimination. The Rasch model assumes that

items are conditionally independent of each other given an individual's propensity (Embretson & Reise, 2013). If this assumption holds, we can assume that the latent variable explains the observed relationship between the items. If another dimension accounts for the relationship between items, this would inflate the precision of the scale and distort item parameter estimates (e.g., larger slope estimates). One way to determine whether the data meets this assumption is to calculate bivariate correlations between item residuals. According to Rasch assumptions, the residuals should be random (and have no relation to each other) since any relation between items is due to the latent trait. All residual correlations were less than or equal to 0.16 for Wave 1 and less than or equal to 0.20 for Wave 4. Morizot, Ainsworth, and Reise (2007) suggest a 0.2 cutoff, evidencing that local independence is tenable.

Multivariate normality assumption. We completed residual analyses in SPSS to test whether our residuals meet the assumption of normal distribution. We tested this assumption with inspection of the skewness and kurtosis measures, visual inspection of histograms, and Q-Q plots. Results showed that our latent variable for overall offending did not meet our assumption of multivariate normality at the person level of Wave 1 or Wave 4. Our latent variable for specialization violated the assumption at the person level of Wave 1. Therefore, we reported the robust standard errors for our HLM results since they provide significance tests of regression coefficients that do not depend on this assumption (Raudenbush and Bryk, 2002: 276–78).

Wave 1 Multilevel Modeling

Estimating random effects of specialization and overall offending. We calculated z tests to determine whether observed differences in specialization and overall offending, at

both individual level and school level of analysis, are greater than would be expected by chance. For this purpose, we estimated a null model without covariates and divided the variance components by their standard error. The ratio is assumed to be approximately normally distributed (Raudenbush & Bryk, 2002). In the current study, variance components at the second level of our model described variation in the latent variables among respondents within schools. The variance components at the third level of our model described the variation across schools.

Z-scores were significant for all four random effects at a significance level of p-value less than 0.001. The results of these z tests were definitive at the person level of analysis, with a z-score of 24 for specialization and a z-score of 26 for overall offending. Comparatively, the z-scores for random effects of specialization and overall offending were significant but smaller at the school level of analysis, respectively 4.5 and 3.8. These results supported our hypothesis that respondents significantly differ in their tendency to endorse violent versus nonviolent offenses (Hypothesis 1). We also observed significant variation in specialization between schools, suggesting that environmental or contextual factors might account for observed differences in specialization. Furthermore, the observed variance components for the random effect of specialization (3.5 at level 2, 0.49 at level 3) were much larger compared to the variance components for the random effect of overall offending at both levels of analysis (1.16 at level 2, 0.07 at level 3).

The intraclass correlation (ICC) is an index that indicates the degree of within cluster dependency (Raudenbush & Bryk, 2002). A high ICC in the present study indicates a higher degree of correlation among respondents' values on our latent variables within schools compared to values obtained from different schools. In other words, it tells us the advantage

of including a third level of analysis. The ICC is computed for each random effect by dividing the variance component associated with the random effect in the school level by the sum of the variance component in the school and person level (Raudenbush & Bryk, 2002). The ICC calculated for the latent variable of specialization equaled 0.12, indicating 12% of the specialization variance is at the school level and 88% at the individual level. The ICC calculated for the latent variable of overall offending equaled 0.06, an estimated 6% of the variance accounted for at the school level. Clearly, it is important to consider clustering effects when studying specialization.

Explanatory variables and specialization. We examined the relationship between latent specialization to several explanatory variables, including demographic covariates, neuropsychological factors, peer risk factors, and environmental criminogenic factors. Backward elimination was utilized to obtain a final model with the best fit per the deviance statistic. The deviance statistic compares the log likelihood of nested models, which is provided in HLM output, to determine if additional predictors significantly reduce the deviance. The distribution is chi-square, and the degrees of freedom are equal to the number of additional parameters in the larger model (Raudenbush & Bryk, 2002). Results of our final model, including fixed effects at level 2 and level 3 and value of R-square (the amount of variance in random effects explained by covariates) at their respective levels, are shown in Table 6. We also included the variance components of our latent measures while controlling for covariates in Table 6. The coefficients for specialization indicated the change in the log odds of specialization in violent versus nonviolent offenses with a one-unit increase in the covariate. A positive coefficient indicated an increase in the ratio of violent to nonviolent

offenses (with greater odds of violent offense), whereas a negative coefficient indicated a decrease in this ratio (with greater odds of nonviolent offense).

The results supported our hypotheses in part. We observed that neuropsychological factors, including lower verbal ability, learning disability, and low birth weight significantly related to greater tendency for violent versus nonviolent offenses while controlling for academic achievement (i.e., grade point average). However, the rate of violent crime arrests was not significant at the school level of analysis as expected. The rate of property arrests was significantly associated with an increase in the tendency to commit nonviolent offenses between schools, though the effect appears to be small. We expected that schools with a higher proportion of persons in poverty would have greater mean specialization in nonviolent offenses, but we observed that an increase in poverty related to an increase in the odds for specialization in violent offenses between schools. One might conclude that schools with higher concentrated poverty have higher overall crime, but this is not the case in the Add Health sample. We observed that poverty was not significantly related to mean propensity for overall offending at the school level. Altogether, proportion of poverty and property arrests accounted for 92% of the variance in specialization between schools. Peer risk factors, more specifically the level of marijuana use and alcohol use among respondents' closest friends, was not significantly associated with increased odds for specialization in nonviolent offenses as expected; however, it did show significant relations to overall offending (described below).

In regards to demographics, our results showed a greater propensity to specialize in nonviolent offenses among females and individuals who self identify with a mixed racial background. Respondents who self identified as African American or Black were

significantly more likely to specialize in violent offenses compared to all other racial identities. In addition, lower parent educational attainment related to specialization in violent offenses. Altogether, fixed covariates accounted 14% of the variance in specialization between individuals.

Explanatory variables and overall offending. We examined the relationships between study covariates with overall offending to investigate whether their pattern of association with overall offending differs from their pattern of associations with specialization. We did not include a-priori hypotheses for these relationships since these variables were chosen for their expected relationship to specialization, which is the main purpose of our study. Results can be observed in Table 6. The regression coefficient indicates the increase in log odds of committing each offense for each one-unit increase in the explanatory variable. The results demonstrated differences in the pattern of relationships to overall offending compared to specialization among more than half of the covariates included in our final model.

Age, racial identity, neuropsychological factors, and peer risk factors demonstrated differing relationships to overall offending compared to specialization. Age of respondents was negatively correlated with the overall propensity to offend, suggesting that the rate of offending decreases between individuals as the age of respondents increases in our sample. This supports the common finding that crime peaks in adolescence and tends to decrease, on average, with age (e.g., Farrington, 1986). Age was not significantly related to our latent variable for specialization. Respondents who identified as Native American or African American/Black demonstrated a higher propensity to offend compared to all other racial identities on average. We also found that marijuana use and alcohol use among peers was

associated with a higher propensity to offend overall. Altogether, fixed covariates accounted for 35% of the variance in overall propensity to offend between individuals.

The observation that neuropsychological factors did not demonstrate significant relations with overall offending further supports our hypothesis that these factors are uniquely related to violent offending. The significant relationship between peer drug use (a proxy for deviant attitudes among peers) with propensity for overall offending suggests that the common finding relating peer nonviolent delinquency to violent offending may be confounded by overall rates of offending. Environmental factors did not demonstrate significant associations with overall offending at the school level of analysis, suggesting that concentrated poverty is more strongly associated with a higher proportion of violence between schools. On the other hand, GPA and parent education were not uniquely related to specialization, although the latter association was weaker for overall offending.

Wave 4 Multilevel Modeling

Estimating random effects of specialization and overall offending. We estimated a two-level hierarchical logistic model without covariates to obtain the significance of individual differences in specialization and overall offending at Wave 4. We obtained z test statistics of the variance component estimates. z-scores were significant for both random effects at a significance level of p-value less than 0.001. The variance component and respective z-score for the random effect of specialization (vc=1.84, z=12) was much larger compared to the random effect of overall offending (vc=0.21, z=4.8).

Explanatory variables and specialization. We examined the relationship between latent specialization to several explanatory variables, including demographic covariates, early neuropsychological factors, and environmental criminogenic factors. Backward elimination

was utilized to obtain a final model with the best fit per the deviance statistic. Results of our final model, including fixed effects, variance components associated with random effects (while controlling for covariates), and R-square values, are shown in Table 7. As stated previously, the coefficients for specialization indicate the change in the log odds of specialization in violent versus nonviolent offenses with a one-unit increase in the covariate. A positive coefficient indicated an increase in the ratio of violent to nonviolent offenses (with greater odds of violent offense), whereas a negative coefficient indicated a decrease in this ratio (with greater odds of nonviolent offense).

The results of our analysis at Wave 4 demonstrated important but few significant relationships between explanatory variables and specialization, with fixed covariates accounting for only 9% of the variance in specialization between individuals. Respondents with a higher educational attainment were significantly more likely to specialize in nonviolent offenses, whereas respondents with a lower educational attainment demonstrated a greater tendency for violent offenses. Consistent with our results at Wave 1, respondents who identified as African American or Black demonstrated a higher log odds for specialization in violent offenses compared to all other racial identities. While concentration of poverty did not significantly relate to specialization as observed at Wave 1, the level of total unemployment demonstrated a significant positive relationship to specialization at Wave 4. This variable is disaggregated (due to unavailable clustering data) but suggests that respondents living in an area with high unemployment are more vulnerable to specialization in violence. Previous research has suggested that areas with higher unemployment typically demonstrate higher levels of violent gang activity (e.g., Kyriacou, Hutson, Anglin, Peek-Asa,

& Kraus, 1999), which might explain the observed relationship between unemployment rate and specialization in violence.

Altogether, our results from Wave 1 and Wave 4 suggest that our explanatory variables do not demonstrate consistent relations to latent specialization over time. We expected that early neuropsychological factors (e.g., low birth weight, learning disability, verbal ability) would continue to predict specialization in violent offenses in adulthood as observed in adolescence. However, our results suggest that early neuropsychological factors and specialization weakens over time, as these covariates did not reach significance in our model at Wave 4. In addition, gender was not a significant predictor of specialization at Wave 4.

Explanatory variables and overall offending. We examined the relationships between study covariates with overall offending to investigate differences in their pattern of association with overall offending compared to specialization. Fixed effects of our final model are summarized in Table 7, accounting for an estimated 28% of the variance in propensity for overall offending between individuals. The results demonstrated differences in the pattern of relationships to overall offending compared to specialization at Wave 4, with no overlap in significant relations among the covariates included in our final model. Similar to Wave 1, age demonstrated a negative relationship to overall offending, with older age associating with lower propensity to offend overall. Females and individuals with higher household income also tended to demonstrate a lower propensity for offending.

Stability of Specialization and Overall Offending Measured Over Time

In order to estimate the stability of our measures of specialization and overall offending across time, we estimated an expanded version of our two-level statistical model

that included offense items and SPEC, our contrast variable representing the balance of violent to nonviolent offenses within individuals, from both waves of data. We were able to estimate four random effects at the person level of analysis and, by including items from both waves in our model, our latent variables are on the same scale.

We define stability as the correlation of our latent variable with itself over time. HLM output provides the correlations among any random effects. The correlations between the four random effects in our expanded model are displayed in Table 8. Results demonstrate that the latent variable for specialization has moderate stability, with a positive correlation over an average of 13 years between measurement points. Interestingly, our latent variable for overall offending was highly negatively correlated over time. This result is difficult to interpret since we did not include latent analyses of offense trajectory classes. We might consider that a large proportion of the sample desisted into adulthood, as is often the case in research on developmental trajectories of offending (e.g., Farrington, 1986). We also observed a moderate negative correlation between the latent variable for specialization at Wave 1 and the latent variable for overall offending at Wave 4. However, our measures for overall offending and specialization were moderately to highly correlated within measurement time points, supporting the common finding that high-rate offenders also commit violent offenses at a higher rate; although this relationship appeared to weaken in early adulthood. Altogether, results suggest that the relationship between overall offending and specialization differs when measured across time. It is tenable to suggest that specialization in offending is predictive of future specialization, whereas the overall propensity to offend demonstrates a more complicated relationship over time.

Discussion

The present study had four primary aims: to determine (a) whether individuals differ systematically in their pattern to commit violent versus nonviolent offenses (i.e., specialize); (b) whether there is stability in the measurement of specialization and overall offending across our two measurement points (i.e., the correlation between random effects); (c) which demographic covariates, neuropsychological factors, peer risk factors, and environmental criminogenic risk factors that may relate to specialization; and (d) differences in the pattern of relationships between explanatory variables and individual differences in overall offending compared to specialization. The random effects for specialization and overall offending were significant at both Wave 1 and Wave 4, supporting our hypothesis that individuals differ systematically in their tendency to commit violent versus nonviolent offenses (i.e., specialization). We found greater variation in specialization compared to overall offending at Wave 1 and Wave 4. This finding implies more substantial differences in the underlying tendencies toward violent versus nonviolent offending among participants in the Add Health sample. We also observed that differences between schools accounted for 12% of the variance in specialization, which is a considerable amount.

In regards to stability in the measurement of specialization, we found a moderate positive correlation between our measure of specialization at Wave 1 and our measure for specialization at Wave 4, spanning an average of 13 years between the measurement points. Comparatively, our measure for overall propensity to offend in adolescence (Wave 1) was on average not predictive of overall propensity to offend in early adulthood (Wave 4). Our latent variables were highly correlated within time points, suggesting that high rate offenders are more likely to commit violent offenses at a higher rate than nonviolent offenses that is

separate from their overall rate of offending. The relationship between specialization and overall offending, however, appears to be more complicated over time. While Osgood and Schreck (2007) suggested that specialization may increase with age, we found a greater degree of individual differences in specialization during adolescence compared to adulthood. One significant difference is that Osgood and Schreck utilized adolescent samples, whereas the Add Health sample spans adolescence (average age of 15 years) and early adulthood (average age of 28.5 years). Our finding combined with the stability in our measurement over time suggests that adolescents tend to demonstrate an underlying tendency towards either violent or nonviolent offenses that persists. Future research can help untangle the relationship between propensity for specialization and overall offending over time by examining different trajectories.

We were also interested in explanatory variables that might relate differentially to violent versus nonviolent specialization. We expected that early neuropsychological factors and community violent crime rates would predict specialization in violent offenses; we found support for the relationship between neuropsychological factors and a tendency to commit greater proportion of violent over nonviolent offenses in adolescence, but this effect did not reach significance in adulthood. We expected that specialization in nonviolent offenses would relate to socioeconomic disadvantage at both individual and school level with the rationale that individuals with greater socioeconomic advantage would have less incentive to commit nonviolent offenses, such as theft, but found the opposite: concentrated poverty predicted greater specialization in violence between schools at Wave 1 and higher unemployment rates predicted greater specialization between individuals at Wave 4. Furthermore, there was a negative relationship between educational attainment of

respondents and specialization at Wave 4 such that when individuals with higher levels of education offend, they are more likely to commit nonviolent offenses at a higher rate than violent offenses. One might conclude that this observation is due to a higher average rate of overall offending among more socioeconomically disadvantaged individuals, but this was not the case in the Add Health sample. Generally, greater socioeconomic disadvantage among individuals and concentrated socioeconomic disadvantage within Census tracts demonstrated unique relations with specialization, with greater disadvantage increasing the odds for a higher proportion of violent to nonviolent offenses. Even more meaningful, the proportion of persons in poverty accounted for 72% of the variance in specialization between schools, and the rate of property crime arrests, which related to higher odds of specialization in nonviolent offenses, accounted for an additional 20% of the variance. While our analyses examined aspects of socioeconomic disadvantage individually, to consider them as single concurrent effects is too narrow and does not adequately represent what it means to grow up in an area that is truly disadvantaged. For example, our study showed that the proportion of individuals living in poverty was strongly associated with higher levels of unemployment within Census tracts. Future research might consider the effects of a concentrated disadvantage index on specialization as we know that neighborhood poverty is strongly associated with other ecological characteristics, including proportion of single-parent families, racial segregation, higher mortality and crime rates (Massey, 1990).

The current study has multiple limitations that deserve mention. First, our study utilized a self-report measure of offending. Although Add Health used computer survey methods shown to maximize reporting among adolescents (Turner, Rogers, et al., 1998), self-report measures are susceptible to invalid responding. Comparisons of self-report and official

arrest records have generally found higher rates of serious offending (Loeber, Farrington, Stouthamer-Loeber, & White, 2008) and a greater degree of specialization (Lynam, Piquero, and Moffitt, 2004; Sullivan et al., 2006) among self-report than was obtained by arrest records alone. This fact, combined with the greater sensitivity of our method of analysis, larger sample size and, therefore, greater power to detect a statistically significant difference might explain why we were able to find significant specialization in our study. Second, our model defines specialization as the relative balance of violent and nonviolent items among the offenses that individuals endorse and does not reflect quantity or severity of offending. This approach allows us to distinguish an individual's tendency to specialize from their overall tendency to offend as well as makes use of all available data regardless of the number of offenses that individuals endorse by implementing our measurement model within a random effects hierarchical logistic regression model. Third, we estimated fixed effects of covariates for the cohort separately at Wave 1 and Wave 4, so direct comparison of coefficients for fixed effects across measurement points is not advisable since the latent variables are not on the same scale in these models (e.g., Table 6 and Table 7). To make direct comparisons across time points, fixed effects should be added to an expanded (i.e., stacked) version of our two-level statistical model, such as the model we specified to estimate the stability of our measures over time. Fourth, we did not examine differences in the functioning of items across groups in our measurement models. Our one-parameter IRT model assumes that items are equal in difficulty across different groups. Future research should consider differences in item functioning across demographic groups, such as by gender or racial identity; this might help explain the higher odds for specialization in violent offenses among individuals who self-identified as African American or Black. Information

on mapping individuals to neighborhood structure at Wave 4 was unavailable at the time of this writing. Thus, our model did not take the nested effects of neighborhoods (i.e., differences between neighborhoods) into account when examining individual differences in specialization or overall offending.

Use of the Add Health sample for our purpose has additional limitations. The sample, while vast, began data collection in 1994. Today's youth are exposed to a very different political and media climate compared to the Add Health cohort, which is over two decades older. The link between exposure to violence in the media (e.g., video games) and increases in aggression is well known (see Anderson & Bushman, 2002), and youth are increasingly using online social media as a space for perpetrating interpersonal aggression (see Patton et al., 2014). Furthermore, as our culture's consumption of TV and screen media has dramatically increased over the past decade, researchers are interested in the effects on children's cognition. For instance, the American Academy of Pediatrics (2016) recommended that parents avoid the use of screen media (other than video chatting) with children less than 18 months old due to the demonstrated detrimental effects on cognition and language acquisition. Future research should consider the role of media consumption in the relationship between neuropsychological factors and violence. Secondary analyses are always limited in the range of variables that can be studied; our analysis of explanatory variables was preliminary and may provide some directions for future analyses of longitudinal designs to expand upon.

Altogether, our results provide several points in support of the existence of specialization in violent versus nonviolent offenses as a phenomenon that is measurable, separate from the overall rate of offending and base rates, and endures over time. Our study

provides preliminary evidence in regards to understanding individual characteristics that contribute to this phenomenon. While neuropsychological factors increased the odds for violent specialization during adolescence, these individual characteristics do not demonstrate consistent relations to specialization over time. Moffitt's life-course persistent typology suggests that their persistent offending is pathological and rooted in the interplay between biology (e.g., neuropsychological deficits) and criminogenic environments. It makes sense that risk factors for specialization in violent versus nonviolent offending would change as individuals develop, as each developmental period presents with different challenges and important social contexts. For example, opportunities for employment are likely to be more relevant during adulthood, while graduation rates and gang violence is likely to be more relevant during adolescence. We conclude that considering context is even more important in research on specialization or specific types of crime than the overall propensity to offend. Future research should also move towards examining potential causal effects, such as the effect of moving out of a neighborhood or school with concentrated disadvantage on individual offending patterns, as this could provide valuable insight for community interventions and policy.

Table 1. Descriptive Statistics of Study Covariates

	Wave 1		Wave 4	
	Mean	**SD**	**Mean**	**SD**
Individual-Level Variables				
Age	15.7	1.74	28.53	1.78
Gender (Male=0; Female=1)	0.495	0.5	0.47	0.49
Family On Public Assistance	0.47	0.88		
Parent Education	2.69	1.27		
Non-English Speaking Home	0.11	0.32		
Total Household Income	N/A	N/A	8.07	2.64
Peer Drug Use	0.63	1		
Peer Alcohol Use	1.1	1.17		
Low Birth Weight	0.06	0.24		
Learning Disability	0.13	0.34		
Verbal Ability	2.6	0.63		
GPA	2.75	0.77		
Educational Attainment	N/A	N/A	5.53	1.99
School/Neighborhood-level				
Proportion Persons Below Poverty Level In 1989	0.15	0.12	0.15	0.19
Property Crimes Per 100,000*	4837	2246	378	197
Violent Crimes Per 100,000*	558	226	155	107.85

**Estimates for Wave 1 include both adult and juvenile arrest rates. Wave 4 estimates include adult arrest rates only.*

Table 2. Rates of Endorsement for Offense Items

Violent Items	**Wave 1**	**Wave 4**
Serious Fight	32.00%	5.10%
Group Fight	20%	3.20%
Seriously Injured Someone	18.70%	--
Threatened With Weapon	4.90%	2.5%
Armed Robbery	4.30%	0.80%
Shoot Or Stab Someone	2%	1.10%
Nonviolent Items	**Wave 1**	**Wave 4**
Check Forgery	--	1.90%
Buying/Selling Stolen Goods	--	2.70%
Credit Card Theft	--	0.70%
Truancy	30.20%	--
Theft	21.80%	4.60%
Graffiti	9.20%	--
Running Away	8.80%	--
Selling Drugs	7.70%	4.20%
Burglary	5.20%	0.70%
Sex Work	1.40%	--

Table 3. Results Of Factor Analysis With Tetrachoric Correlation

Item Label	**Wave 1**	**Wave4**
Serious Fight	0.66	0.71
Group Fight	0.71	0.68
Armed Robbery	0.81	0.82
Threatened With Weapon	0.81	0.68
Shoot Or Stab Someone	0.8	0.6
Seriously Injured Someone	0.7	---
Truancy	**0.39**	---
Running Away	**0.51**	---
Graffiti	0.68	---
Theft	0.67	0.68
Burglary	0.71	0.81
Destruction Of Property	0.66	0.71
Sex Work	**0.45**	---
Selling Drugs	0.73	0.67
Check Forgery	---	**0.46**
Buying/Selling Stolen Goods	---	0.73

Table 4. IRT Results For Wave 1

Item Label	2 Parameter Model		1 Parameter Model	
	Difficulty (s.e.)	**Discrimination (s.e.)**	**Difficulty (s.e.)**	**Discrimination (s.e.)**
Serious Fight	0.60 (0.013)	1.98 (0.053)	0.62 (0.012)	1.91 (0.019)
Group Fight	1.11 (0.017)	2.02 (0.049)	1.13 (0.015)	1.91 (0.019)
Seriously Injured Someone	1.14 (0.023)	2.13 (0.056)	1.19 (0.015)	1.91 (0.019)
Theft	1.16 (0.022)	1.56 (0.041)	1.05 (0.014)	1.91 (0.019)
Damage Property	1.31 (0.023)	1.71 (0.046	1.24 (0.015)	1.91 (0.019)
Graffiti	1.82 (0.031)	1.85 (0.053)	1.79 (0.020)	1.91 (0.019)
Threatened Weapon	1.99 (0.032)	2.58 (0.094)	2.26 (0.026)	1.91 (0.019)
Sell Drugs	1.99 (0.035)	1.79 (0.053)	1.93 (0.21)	1.91 (0.019)
Armed Robbery	2.14 (0.036)	2.38 (0.083)	2.35 (0.028)	1.91 (0.019)
Burglary	2.16 (0.039)	2.00 (0.063)	2.21 (0.025)	1.91 (0.019)
BIC	131676		131807	

Table 5. IRT Results For Wave 4

Item Label	2 Parameter Model		1 Parameter Model	
	Difficulty (s.e.)	**Discrimination (s.e.)**	**Difficulty (s.e.)**	**Discrimination (s.e.)**
Serious Fight	1.96 (0.043)	2.59 (0.129)	2.09 (0.032)	2.18 (0.043)
Group Fight	2.2 (0.048)	2.73 (0.138)	2.39 (0.039)	2.18 (0.043)
Damage Property	2.31 (0.057)	2.02 (0.091)	2.23 (0.035)	2.18 (0.043)
Sell Drugs	2.4 (0.064)	1.83 (0.084)	2.22 (0.034)	2.18 (0.043)
Stolen Goods	2.46 (0.062)	2.24 (0.109)	2.49 (0.041)	2.18 (0.043)
Theft	2.49 (0.078)	1.63 (0.081)	2.16 (0.032)	2.18 (0.043)
Threatened Weapon	2.52 (0.072)	2.26 (0.137)	2.55 (0.04)	2.18 (0.043)
Armed Robbery	2.65 (0.065)	3.46 (0.263)	3.13 (0.064)	2.18 (0.043)
Shoot/Stab Someone	2.85 (0.09)	2.48 (0.154)	3.02 (0.056)	2.18 (0.043)
BIC	33130		33180	

Table 6. Hierarchical Linear Modeling Results for Wave 1: Fixed Effects

Level-2 Fixed Effects	**Specialization**		**Overall Offending**	
	Coefficient	**SE (Robust)**	**Coefficient**	**SE (Robust)**
Parent Education (reverse-coded)	0.23**	0.02	0.07**	0.02
Age			-0.06**	0.01
Gender (0=male)	-0.18*		-0.38**	0.03
African American or Black	0.83**	0.09	0.30**	0.04
Native American			0.26*	0.08
Other Racial Idenity	-0.54**	0.14		
Verbal Ability	0.15*	0.05		
Learning Disability	0.25**	0.07		
Low Birth Weight	0.23*	0.07		
GPA	-0.16**	0.04	-0.16**	0.02
Peer Marijuana Use			0.19**	0.02
Peer Alcohol Use			0.11**	0.01
R-Square:	0.14		0.35	
Level-3 Fixed Effects				
Proportion of Population in Poverty	1.47**	0.32		
Property Arrests Per 100,000	-2.9xE^4	1.0xE^5		
R-Square:	0.92			
Covariance Components	**Specialization**		**Overall Offending**	
Intra-tract variance	3		0.75	
Inter-tract variance	0.04		0	

Table 7. Hierarchical Linear Modeling Results For Wave 4

Level-2 Fixed Effects	**Specialization**		**Overall Offending**	
	Coefficient	**SE (Robust)**	**Coefficient**	**SE (Robust)**
Age	0.05	0.03	-0.04*	0.01
Gender (0=male)	-0.19	0.11	-0.25**	0.05
Household Income			-0.03**	0.008
Educational Attainment	-0.12**	0.02		
African American Or Black	0.22*	0.1		
Total Unemployment Rate (Census Tract)	2.44*	0.8		
R-Square:	0.09		0.28	
Covariance Components (Controlling For Covariates)				
Intra-Tract Variance	1.67		0.15	

Table 8. Correlation Among Wave 1 and Wave 4 Measures

	Overall Offending		Specialization	
	Wave 1	**Wave4**	**Wave 1**	**Wave 4**
Overall Offending				
Wave 4	-0.53* (0.02)	1		
Specialization				
Wave 1	0.94* (0.008)	-0.6* (0.02)	1	
Wave 4	0.42* (0.02)	0.5* (0.02)	0.38* (0.02)	1

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