Published in final edited form as:

Vict Offender. 2018 ; 13(1): 28–47. doi:10.1080/15564886.2016.1250691.

Patterns and Correlates of Offender Versatility and Specialization across a 23-Year Span for At-Risk Young Men

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Abstract

This study examined patterns and correlates of offender specialization versus versatility, or more random offenses, among 206 at-risk men. Both official records and self-report data of offending from late childhood to ages 31/32 were used. Aggregate-level and individual-level analyses indicated that the predominant offender pattern for this sample was versatility. Three correlates of offender versatility were examined (offense frequency, early onset, gang association). Aggregate-level findings consistently revealed offense frequency as a robust correlate of offender versatility, whereas individual-level findings differed among the three measures of offender versatility. The congruence of these findings with predictions from Patterson's (1982) coercion model is discussed.

Keywords

longitudinal; offender specialization; offender versatility

The degree to which offenders specialize in a particular type of crime during their criminal career has drawn considerable attention in criminological research because it carries important implications for both theory and public policy. If offenders show complete generality (or versatility), then general theories of crime, interventions, and justice decision-making efforts that do not differ as a function of the given crime type may be sufficient. On the other hand, if the predominant pattern is offender specialization, then theories and public policy measures that focus on specific crime types are called for. Whether some offenders tend to specialize in specific types of crime (e.g., violent crimes) is of particular interest, and whether such specialization tendencies can be identified, is the topic of the present study.

Some criminological theories anticipate or imply high versatility across the criminal career of offenders (e.g., Agnew, 1992; Akers 1994; Gottfredson & Hirschi, 1990). Similarly, the coercion model of Patterson and colleagues (Patterson, 1982; Patterson, Reid, & Dishion, 1992) predicts that the violent offender is a member of a broader category of multiple offender, and thus that violence is a manifestation of high rates of antisocial behavior (Capaldi & Patterson, 1996). Others, including differential opportunity theory (e.g., Cloward & Ohlin, 1960) and an integrated structural-marxist perspective (e.g., Colvin & Pauly, 1983), are more consistent with the notion that offenders specialize in certain types of crime throughout their career. A third group of theories occupies a middle ground and hypothesizes some extent of specialization for either certain clusters of criminal behavior (e.g., the rational choice theory from Clarke and Cornish, 1985) or a subset of offenders, such as adolescence-limited offenders (Moffitt, 1993), and a fairly high degree of versatility for another subset of offenders, such as life-course persistent offenders (Moffitt, 1993).

Empirical research has generally provided evidence of versatility in offending across criminal careers, especially among frequent offenders, combined with a small degree of specialization in certain types of crime (including burglary, drugs, and auto theft) for small subsets of offenders (Armstrong, 2008a; Blumstein, Cohen, Das, & Moitra, 1988; Britt, 1996; Cohen, 1986; Farrington, Snyder, & Finnegan, 1988; Piquero, Farrington, & Blumstein, 2007). Further, some evidence has been found of a change in the tendency to specialize over time among persistent offenders (Armstrong, 2008b). Last, results also suggest that offenders tend to concentrate their criminal activities within broader categories or domains of crime (i.e., nonviolent more so than violent; Cohen, 1986; Piquero, Farrington, & Blumstein, 2003).

Fisher and Ross (2006), among others, argued that these general patterns may be somewhat misleading because certain methodological features in extant research might have contributed to an underestimation of specialization in offender careers. First, most studies have relied on official data on offending, rather than on self-report measures. It is well-known that official crime data represent only a small subset of all offenses (Elliott & Voss, 1974; Gold, 1966). They also may overrepresent more serious, violent crimes that receive a higher focus of police attention and are solved or cleared at higher rates (Federal Bureau of Investigation, 2001). Interestingly, Lynam, Piquero, and Moffitt (2004) found evidence for offender specialization in violent crime when using self-reports but not when using official records data on crime.

Second, studies differ in the number of offense categories and the way that offenses are classified. Broad offense categories (such as violence, property, and drug offenses) may yield higher estimates of offender specialization than more fine-grained categories, and selection of the most serious offense to represent a multi-offense episode can yield higher estimates of offender specialization compared to placement of multi-offense episodes into a separate “combination” category (Fisher & Ross, 2006).

Third, different methodological conceptualizations of offender specialization have been used. Each requires specific data structures that are subject to their own inherent limitations (Osgood & Schreck, 2007). Some techniques (e.g., forward specialization coefficient) focus

on *sequential* specialization (Brennan, Mednick, & John, 1989), which requires time-ordered offense data that are typically unavailable in self-reports. Others (e.g., binomial distribution modeling) obviate the need for time-ordered offense data because they focus on *distributional* specialization (Brennan et al., 1989), that is, whether the probability of committing a specific type of offenses (e.g., violent crimes) increases as the total count of offenses increases.

Fourth, different time spans have been used (see Sullivan, McGloin, Pratt, & Piquero, 2006). Often, fairly broad time spans, such as year-to-year data collection waves or longer, are used (Sullivan et al., 2006), albeit few studies have followed their participants beyond age 18 (Piquero et al., 2007). Broad time spans may mask short-term offender specialization. Sullivan et al. (2006) have coined the term “time aggregation effects” for this phenomenon.

Fifth, most studies have employed aggregate-level (i.e., sample-level) measures of specialization (Osgood & Schreck, 2007; Sullivan, McGloin, Ray, & Caudy, 2009), such as transition matrices, forward specialization coefficient, or binomial distribution modeling. Few studies to date have used individual-level measures of specialization (e.g., diversity index) that capture within-person patterns of offending. Findings based on aggregate-level measures limit the ability to evaluate important predictions from life-course theories of crime about offender specialization (e.g., those posited by Moffitt, 1993; 1994). The predominance of this approach has likely produced an incomplete picture of the extent to which offenders specialize (Sullivan et al., 2006). Because of such concerns, newer individual-level techniques such as latent class analysis, multilevel item response theory modeling, and nonparametric regression have increasingly been applied to the examination of offender specialization in recent years (e.g., Baker, Metcalfe, & Jennings, 2013; Brownfield & Sorenson, 1987; Hagan, Gillis, & Brownfield, 1996; Nieuwbeerta, Blokland, Piquero, & Sweeten, 2011; Osgood & Schreck, 2007; Raudenbush, Johnson, & Sampson, 2003; Sullivan et al., 2009). To date, no consensus exists on the best way to measure specialization; each approach offers unique insights into the extent, nature, or form of offender specialization (Sullivan & McGloin, 2014; Sullivan et al., 2009).

Study Aims

Clearly, there are some important gaps in our understanding of offender specialization. Because no single study can address all discussed methodological concerns simultaneously, the current study focused on two issues that are relatively underresearched. A unique strength of our dataset is the availability of three measures of crime (self-reports, official convictions, official arrests) that were collected for an at-risk community sample of 206 men across an unusually long time span (from late childhood until ages 31/32). Therefore, the first study question examined whether the patterns and correlates of offender specialization and versatility would be consistent across self-report and official record measures of crime. Results for the Dunedin cohort (Lynam et al., 2004), which revealed offender specialization in self-reports but not in official record data, suggest that we should anticipate limited consistency across our crime measures.

The second study question examined whether the patterns and correlates of offender specialization and versatility would be consistent across an aggregate-level (the binomial distribution) and an individual-level (the diversity index) measure of offender specialization. Not many longitudinal datasets are able to address this question using three measures of crime. Because one of the three crime measures was based on self-report data, we used an aggregate-level measure that does not require time-ordered data. The diversity index was deemed the strongest individual-level measure for our purposes because two of the three crime measures were derived from official records, which typically results in fairly sparse data for community samples of this magnitude (newer individual-level measures tend to require very large sample sizes and thus were not a good choice). Results from Piquero, Paternoster, Mazerolle, Brame, and Dean (1999), who compared forward specialization coefficient findings to those from the diversity index, suggest that we should expect a great deal of consistency.

The current study was guided by Patterson's coercion model (e.g., Patterson, 1982; Patterson, Reid, & Dishion, 1992) which purports that engagement in violent crime is more likely among high-frequency (aka versatile) offenders (Capaldi & Patterson, 1996). Hence, engagement in violent crime should be related to the same correlates as versatile offending. Guided by this framework, this study focused on three correlates (i.e., total count of offenses, early onset of offending, gang association). *Total count of offenses* was included because the frequency of offending has been found to be related to offender versatility and violent offending in many studies (e.g., Chaiken & Chaiken, 1982; McGloin, Sullivan, Piquero, & Pratt, 2007; Monahan & Piquero, 2009; Piquero et al., 2007). Yet, some work has suggested that the relation between frequency of offending and specialization may not be as robust as generally assumed (Brame, Paternoster, & Bushway, 2004). Nevertheless, we expected that a higher total count of offenses would be related to engagement in violent crime and more offender versatility.

Early onset of offending was included because dual taxonomies of antisocial behavior posit that life-course persistent offenders would commit a wider variety of crimes, including violent crimes, whereas adolescence-limited offenders would primarily engage in crimes that symbolize adult privilege or demonstrate autonomy from parents (Moffitt, 1993, pp. 694–695). Various studies have found empirical support for this contention (Mazerolle, Brame, Paternoster, Piquero, & Dean, 2000; McGloin et al., 2007; Moffitt, Caspi, Harrington, & Milne, 2002; Sullivan et al., 2006), albeit this was not always the case (Piquero et al., 1999; Piquero et al., 2007). On the basis of this literature, we expected that early onset offending would be linked to engagement in violent crime and more offender versatility relative to late onset offending.

Last, Piquero et al. (2003) urged the field to include measures of co-offending because much (especially juvenile) criminal activity is a group phenomenon (pp. 458, 480). Because a direct measure of co-offending was unavailable, we included the *total count of gang association* as an indirect proxy measure. Research has shown that gang membership increases the risk of involvement in violence (e.g., Thornberry, 1998), although not all co-offenders necessarily belong to a juvenile gang (Andresen & Felson, 2012). Based on this

literature, we expected that association with a gang at more assessment waves would be linked to engagement in violent crime, as well as to a more versatile offending pattern.

Method

Sample

Analyses were conducted using data from the Oregon Youth Study (OYS), an ongoing multiagent, multimethod longitudinal study. A sample of boys was selected from schools in the higher-crime areas of a medium-sized metropolitan region in the Pacific Northwest. Thus, the boys were considered to be at heightened risk for later delinquency. Of the eligible families, 206 (74.4%) participated in the OYS. Two successive Grade 4 (ages 9–10 years) cohorts of 102 and 104 boys enrolled in the OYS in 1983–1984 and 1984–1985 (see Capaldi & Patterson, 1987). The average retention rate was 98% through the early 20s, and 94% of living participants remained as part of the panel in Year 20. Participants who moved out of the area were retained in the study, with interviewers traveling to assess them. Both cohorts had very similar demographic characteristics and were combined for analysis. The sample was 90% Caucasian and 75% lower or working class; over 20% received some form of unemployment or welfare assistance in Year 1 of the study (Patterson et al., 1992). Data from all 206 men were used in the current study.

Procedures

Assessment on the OYS was yearly, multimethod, and multiagent, including in-person interviews and questionnaires for self and parents at the Oregon Social Learning Center (each lasting approximately 1 hour), telephone interviews that provided multiple samples of recent behaviors (a total of six, 3 days apart), home observations (a total of three 45-minute observations), videotaped interaction tasks, school data (including teacher questionnaires and school achievement test scores), and court records. Family consent was mandatory. Participants were compensated for their time at each assessment wave.

Measures

Three official records or self-report measures of crime were used in the current study.

Number of official arrests.—Juvenile or adult court record searches were conducted locally for the OYS men each year from ages 9/10 to 31/32 years (i.e., Waves 1 to 23). When families moved to other communities, the local authorities were contacted for permission to conduct record searches in their jurisdictions. The arrest records included the date and type of each offense. From these records, the number of annual arrests was derived for each participant. Each arrest report was counted as a separate offense. In several instances, more than one arrest report was filed on the same day, and each was counted as a separate offense. If multiple charges were included in a report, only the most serious charge was selected. Two types of charges were excluded from analysis: (a) minor traffic infractions such as driving with a broken tail light; (b) contempt of court and other charges for which the actual crime could not be determined.

Number of official convictions.—The arrest records also included information about the court dispositions for the offenses (e.g., dismissal of charges, sentences such as fines, probation, and incarceration). From these records, the number of official convictions was derived for each participant from ages 9/10 to 31/32 years (i.e., Waves 1 to 23).

Number of self-reported delinquent acts.—Systematic collection of self-report data on offending behavior of the study participants began at ages 12/13 years and continued until ages 31/32 years (i.e., Waves 4 to 23), with the exception of ages 26/27 years (i.e., Wave 18) when this information was not collected. At each assessment year, participants filled out the Elliott Delinquency Scale (Elliott, Ageton, Huizinga, Knowles, & Canter, 1983), a self-report scale that was constructed as a parallel measure to the FBI's Uniform Crime Reports arrest measure. A total score of self-reported delinquent acts was formed by summing up the open-ended responses for the items across the 20 years (19 waves) of assessment. The items varied in terms of severity and represented various forms of delinquency, such as theft, property damage, and violence (e.g., set fire to a building, attacked someone with the idea to seriously hurt him or her, had sex with someone against their will). The total score was comprised of 45 items for each of Waves 4–11 and 38 items for each of Waves 12–17 and 19–23. The seven dropped items were not administered in the later assessments (six of these items were school-related offenses such as threatening to hit another student; the seventh was failure to return extra change from a cashier).

Correlates.—In addition to the *total count of offenses* for each outcome measure (i.e., sum of all committed offenses), two other correlates were examined. The *early onset of offending* measure was based on prior work (Patterson & Yoerger, 1993; 1997) and identified those with first arrest before age 14 (1 = Yes, 0 = No). Fifty two (25.2%) OYS men had been arrested prior to age 14. The *total count of gang association* measure was the total number of times from ages 12/13 to 25/26 and 27/28 to 31/32 years at which the OYS men reported that they were a gang member, hung out with gang members sometimes or often, or had been involved in gang fights in the past year. Eighty five (41.3%) OYS men reported gang association at least one time. This rate is higher than what might be expected due to frequent assessment of any gang association across the adolescent and early adult years of the OYS men.

Analytic Approach

As mentioned earlier, this study was guided by the coercion model (Patterson, 1982; Patterson, Reid, & Dishion, 1992) which contends that violent offending is a manifestation of versatile, high-frequency offending (Capaldi & Patterson, 1996). Building on this proposition, the aggregate-level analysis utilized the *binomial distribution approach* to investigate offender specialization and versatility. It assumes that violent crimes are committed at random in criminal careers (Farrington, 1998). If the OYS men specialized in violence across the 23-year period, then the actual number of violent offenders should be significantly fewer than expected, and each offender should commit more violent offenses (on average) than expected (Piquero et al., 2007). In contrast, if there were generality in offending across the study period, then the probability of committing a violent offense should increase with the number of offenses committed.

For the individual level analyses, a *diversity index* was considered to be the strongest approach for the reasons described earlier. Diversity indexes (D) provide an estimate of the probability that any two offenses randomly selected from an individual's offending history belong to two different offending categories. The minimum value of the diversity index is 0, indicating complete specialization in offending. Higher values on the diversity index reflect more diversity, hence more versatility in offending. The maximum attainable value for offending diversity depends on the number of crime categories under analysis and is given by the formula, $d_{\max} = (k-1)/k$, where k equals the number of crime categories (Mazerolle et al., 2000).

For the *Diversity Index Official Arrests*, our calculations were based on the potential cumulative occurrences of 20 crime types (i.e., its maximum value was 0.950): status offenses, burglary, shoplifting, theft, theft of a motor vehicle, fraud/forgery, weapons possession/use, robbery, threatening violence, assault, sexual assault, drug/alcohol offenses, driving/traffic, endangering/mistreatment of a minor, vandalism/criminal mischief, public disorder, trespassing, parole/probation violation, other minor infractions, and other criminal offenses. The calculations for the *Diversity Index Official Convictions* followed the same rationale (i.e., its maximum value was also 0.950). The calculations for the *Diversity Index Self-Reported Delinquent Acts* were based on the potential cumulative occurrences of eight crime types (i.e., its maximum value was 0.875): felony assault, minor assault, robbery, felony theft, minor theft, damaged property, illegal services (such as buying/selling drugs or sex), and public disorder. The differences between the crime type categories for official records versus self-report data were due to the greater detail available from the official records (i.e., official records separately listed threatened versus actual violence and also specified offenses that were not easily combined with other categories, such as trespassing, parole and probation violations, and offenses due to status as a minor).

Results

Aggregate-Level Findings

Similar to findings for the Cambridge Study in Delinquent Development (Piquero et al., 2007), the fraction of all offenses that were violent was fairly low for the OYS men: 0.0998 for official arrest data, 0.0745 for official convictions data, and 0.1889 for self-reported delinquency.

Official arrests.—Table 1 reports the observed and expected violent and non-violent offenses and offenders, shown by number of offenses committed overall. Results are explained in some detail for this crime measure and then summarized for the other two offense measures. For the men committing any offenses the number committed varied from 1 to 42. For the group of offenders who commit n offenses, 0.0998 in violent offenses could be expected if violence were distributed randomly. If different types of offenses were committed at random, it might be expected (see Column 10) that 9.98% of the 37 offenders who committed only one offense would commit a violent crime. As shown in Table 1, the observed number of one-time offenders (4) whose offense was violent (see Column 4) did not differ significantly from the expected number of violent offenders (3.69) shown in

Column 9. For the next category of two committed offenses, it was expected (Column 10) that 18.97% (i.e., a proportion equal to $[1-(0.9002)^2]^1$) of the 19 offenders who committed two offenses would commit at least one violent offense. Again, the actual number of violent offenders (3) (see Column 4) did not differ significantly from the expected number of violent offenders (3.60) shown in Column 9. For the next category of three committed offenses, it was expected (Column 10) that 27.06% (i.e., a proportion equal to $[1-(0.9002)^3]$) of the 17 offenders who committed three offenses would commit at least one violent offense. Again, the actual number of violent offenders (4) (see Column 4) did not differ significantly from the expected number of violent offenders (4.60) shown in Column 9. As can be seen in Column 11 of Table 1, there was a close match between the actual and the expected number of violent offenders at every single total offense count, and thus the Chi-Square tests were non-significant. Furthermore, the overall goodness-of-fit test shown at the bottom of Column 11 also indicated complete generality in offending (63 observed versus 63.41 expected violent offenders among all OYS men actively engaged in offending; $p > .05$). In other words, there was no detectable tendency for specialization in violent crime among the OYS men across the 23-year period according to official arrest data.²

Official convictions.—There also was no evidence for specialization in violent crime among the OYS men across the 23-year period according to official convictions data.³

Self-reported delinquent acts.—Many more offenses were self-reported than were ascertained from official records, ranging from 1 to 9,199 (see Table 2). All but one OYS men self-reported at least one offense across the study period. For the self-report data, 0.1889 in violent offenses could be expected if violence were distributed randomly for the group of offenders who commit n offenses. Nearly all tests (see Column 11 of Table 2), failed to detect evidence for specialization in violent crime across the 20-year period according to self-report data.⁴ Just one exception to this overall result was found. For the first category, the actual number of violent offenders was higher than the expected number (3 versus 0.94) (see Column 4 and 9, respectively), indicating some specialization in nonviolent crime.

¹The value .9002 is the fraction of arrests for nonviolent offenses (see Table 1 note).

²Because the expected number of violent offenders was markedly below five in several categories, we repeated the analysis with collapsed categories to assess whether small expected frequencies might have biased the findings. Yet, the results with collapsed categories paralleled those described so far ($\chi^2[18] = 4.35, p > .05$). In addition, robbery was counted as a violent offense, consistent with prior research (e.g., Capaldi & Patterson, 1996). Because robbery could also be regarded as a nonviolent offense, we repeated these analyses while counting robbery as a nonviolent offense. The fraction of arrests for violent offenses decreased (i.e., $104/1182 = 0.0880$) but the overall substantive conclusion remained the same ($\chi^2[28] = 7.94, p > .05$).

³Because of restrictions to manuscript length, the table of results is not shown but available from the first author on request. The frequency of official convictions ranged from 1 to 29. The fraction of convictions for violent offenses was $47/631 = 0.0745$. The fraction of convictions for nonviolent offenses was $584/631 = 0.9255$. In this case, 0.0745 violent offenses could be expected if violence were distributed randomly for the group of offenders who commit n offenses. All significance tests for individual offense categories were nonsignificant (all $p > .05$). The overall goodness-of-fit test was also nonsignificant ($\chi^2[19] = 10.50, p > .05$). Taken together, these results reveal no evidence for specialization in violent crime for official convictions data. The same conclusion was reached when the analyses were repeated with (1) collapsed categories ($\chi^2[11] = 6.43, p > .05$); and (2) robbery being counted as a nonviolent offense ($\chi^2[19] = 12.30, p > .05$; fraction of convictions for violent offenses = $[38/361] = 0.06$).

⁴The same conclusion was reached when the analyses were repeated while counting robbery as a nonviolent offense ($\chi^2[39] = 10.59, p > .05$; fraction of self-reported violent offenses = $[32,847/176,650] = 0.1859$). Moreover, some OYS men had missing values in the self-reported delinquent act data because they did not participate in all assessment waves. Thus, analyses also were repeated after excluding any men with missing time points. Yet, the overall conclusion remained the same for men with complete self-report data and one or more offenses ($N = 158$; fraction of self-reported violent offenses = $[25,004/145,246] = 0.1721$; $\chi^2[30] = 15.97, p > .05$).

In sum, no evidence for offender specialization was found for the aggregate (sample-wide) analyses of official arrests, official convictions, and self-reported offending.

Correlates of engagement in violent crime.—Next, we examined via logistic regression analysis whether total count of offenses, total count of gang association, and early onset of offending prior to age 14, were associated with engagement in violent crime. We felt that this regression method was a reasonable choice because (1) the framework guiding this study (i.e., Patterson’s coercion model) considers engagement in violent crime to be more likely among high-frequency (versatile) offenders, and (2) our aggregate-level analysis had consistently failed to produce evidence of specialization in violent crime for the OYS men. For Official Arrests and Convictions, engagement in violent crime was coded as 1 = Yes or 0 = No. To avoid a potentially empty cell in the regression of Self-Reported Delinquent Acts, engagement in violent crime was coded as 1 = 2 or more acts, or 0 = 0 or 1 act.

For comparison purposes, each covariate was first regressed separately on each outcome (see first column of Table 3). In the single-predictor models, each of the three predictors was significantly associated with all of the three outcomes. Next, multivariate logistic regression models were estimated for the three outcomes (see second column of Table 3). As can be seen, the multivariate logistic regression models were significant for each outcome. However, only the total count of offenses emerged as a significant predictor of engagement in violent crime in the multivariate models. Specifically, men who had committed a higher number of offenses had a significantly higher risk of becoming a violent offender, and this was the case for each outcome.

Individual-Level Findings

Next, we present the individual-level findings for the OYS men, using the diversity index measures. Note that mean diversity indices were analyzed only for those participants who committed two or more offenses. This ensured that the OYS men who had “0” or “1” offense (and thus could have no diversity in offending) did not contribute to the observed value of the given diversity index. The mean *D* for Official Arrests was 0.68 (*SD* = 0.19, Median = 0.72, Mode = 0.50, Maximum = 0.91) for the OYS men. The mean *D* for Official Convictions was 0.64 and thus slightly lower compared to the value for arrest data (*SD* = 0.19, Median = 0.68, Mode = 0.50, Maximum = 0.89). Finally, the mean *D* for Self-Reported Delinquent Acts was 0.51 (*SD* = 0.21, Median = 0.55, Mode = 0.00, Maximum = 0.83) for this sample. Overall, these mean *D* values represent moderate levels of offender versatility for the OYS men.

Association of correlates with the diversity indices.—Consistent with Sullivan et al. (2006), we used Tobit regression to examine the predictive effects of the three correlates on the diversity scores.⁵ Analyses were conducted using LIMDEP Version 8.0.10 (Econometrics Software, 1996–2003). Substantive findings were the same when the Tobit

⁵Similar to prior research on the diversity index (Mazerolle et al., 2000; Piquero et al., 1999; Sullivan et al., 2006), we used nonparametric tests for comparing mean *D* values across subgroups prior to the estimation of regression models. A table of results is available from the first author on request. Kruskal Wallis χ^2 and Mann-Whitney *U* tests indicated significant mean *D* Official Arrest

regression models were rerun after normalizing transformations were applied to the two *D* Official Records measures to correct for moderate levels of non-normality. For ease of interpretation, findings for the original (i.e., untransformed) diversity indices are presented.

The results of the multivariate Tobit regression models are shown in Table 4. Single-predictor models were run first, and their findings are also shown in Table 4 for comparison purposes. When predicting *D Official Arrest* scores, all three predictors showed significant effects individually, but in the multivariate regression model only total count of offenses and total count of gang association were significant predictors. Specifically, a higher total number of official arrests and a higher total count of gang association across the years were associated with higher scores on the *D Official Arrest* measure (i.e., more versatility in offending). For the *D Official Convictions* measure, nearly identical results were found. The only difference was that, here, the predictive effect of early onset of offending was also significant in the multivariate regression model, whereby early onset of offending before age 14 years was linked to higher scores on the *D Official Convictions* measure (i.e., more offender versatility). Results were quite different for the *D Self-Reported Delinquent Acts* measure. Only one of the three predictors, total count of gang association, showed significant individual and multivariate predictive effects on the criterion. Specifically, a higher total count of gang association across the years was related to higher scores on the *D Self-Reports Delinquency* measure (i.e., more versatility in offending).

In sum, the diversity index analyses indicated moderate diversity in offending for each of the three types of offense measures, and higher diversity was associated with higher counts of offending, early onset of offending, and a higher total count of gang association.

Discussion

The extent to which offenders specialize in specific types of crime (e.g., violent crimes) carries important implications for theory and public policy. As discussed in the introduction, some scholars have argued that prevailing methodological features of much extant research might have contributed to an underestimation of the degree of offender specialization and that individual-level measures may be better suited to examine predictions of life-course theories of crime about offender specialization than are aggregate-level measures. Guided by Patterson's coercion model (Patterson, 1982; Patterson et al., 1992), this study used an at-risk community sample of men to examine the patterns and correlates of offender specialization versus versatility in crime across a 23-year span. Two analytical approaches were applied using three measures of crime.

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differences for each correlate. Specifically, men who had committed relatively few total offenses (i.e., those in the first quartile) showed a much lower level of offender versatility than the men in the other three quartiles ($p < .001$), with the degree of versatility increasing from quartile to quartile. Men with an early first arrest had significantly higher levels of offender versatility than those without early arrest ($p < .001$). Last, men who had reported gang association at a minimum of three time points showed a much higher level of offender versatility compared to those with less frequent gang association ($p < .001$). Similar results were found for *D Official Convictions* (all $p < .001$). However, for *D Self-Reported Delinquent Acts*, only the test statistic for total gang association was significant ($p < .01$). For total count of offenses and early onset, the increases across levels in *D Self-Reported Delinquent Acts* were comparatively smaller and not significant ($p > .05$). The mean *D* was actually lower for the fourth Quartile (highest frequency) offenders versus the *D* for the second and third Quartiles. The nonparametric tests for the self-report data were repeated after excluding any men with missing time points. This did not change the substantive conclusions ($p > .05$ for total count of offenses; $p > .05$ for early onset; $p = .047$ for total count of gang association).

Two main conclusions emerged. First, results consistently revealed versatility as the predominant pattern, with scant evidence pointing toward specialization in the men's offending behavior. The pattern of offender versatility did not differ as a function of data source (self-reports, official records), overall frequency of offending (total count of all committed offenses), and analytical method (aggregate-level, individual-level). Second, the findings regarding correlates or predictors differed for the aggregate-versus individual-level analyses.

As far as the first main conclusion is concerned, it is of interest that our aggregate-level results were partially inconsistent with the Dunedin study (Lynam et al., 2004) which found no specialization in the official records data but specialization in the self-report data. Reasons for the discrepancy likely have to do with the age at follow-up and sample features. The OYS men were followed to ages 31/32; the Dunedin cohort was studied at ages 18 and 21 for the self-report and at age 25 for the official records data. The comparably short time period used in the Dunedin Study likely led to an overestimation of the degree of specialization in the analysis of the self-report data relative to the official records data. This effect might have been exacerbated by the fact that almost half of the Dunedin participants were females who would typically be expected to commit fewer crimes compared to males (see, e.g., Mazerolle et al., 2000). Only a reanalysis of the Dunedin data over longer developmental periods would provide a conclusive answer to these issues. It is, however, reassuring that our aggregate-level study findings were consistent with those from Piquero et al. (2007) who analyzed official records data of the Cambridge study men. Moreover, results for the OYS men revealed that the fraction of violent offenses increased with the number of total offenses committed (the fraction ranged from 0.0745 for official convictions to 0.1889 for self-reported offenses). This is in keeping with the extant literature on the confounding of offender specialization with offense rate (for a discussion, see Osgood & Schreck, 2007) and tenets of Patterson's coercion model.

As stated above, the individual-level findings also revealed a predominating pattern of offender versatility for the OYS men. This is all the more remarkable because our aggregate-level analysis focused on specialization in violent crimes (which is a fairly broad crime domain), whereas a finer lens was applied in the individual-level analysis (where a larger number of crime categories were used). If anything, the individual-level results for the OYS men should have been prone toward showing lesser degrees of offender specialization compared to the aggregate-level findings because more fine-grained offense categories tend to yield lower estimates of specialization than do broad offense categories (see Fisher & Ross, 2006). However, the finding of offender generality for the OYS men was quite robust across analytical methods.

To provide additional context, it may be instrumental to compare the mean *D* values of the OYS men to those observed in other studies because the diversity index has seen scant application in prior research. It is noteworthy that the mean levels on our diversity index measures were rather higher than those observed by Sullivan et al. (2006), Piquero et al. (1999), and Mazerolle et al. (2000). It is difficult to pinpoint the exact reasons for this difference because it likely results from a complex set of methodological and sample features. The latter two studies included both genders, whereas Sullivan et al. (2006) and the

OYS consisted only of males. The assessed time spans were different (e.g., Sullivan et al., 2006, assessed a 36-month period; the OYS men were followed across a 23-year span). Last, the number of crime categories differed among the studies, resulting in differing maximum attainable values on the diversity indices. Piquero et al. (1999) and Mazerolle et al. (2000) distinguished 3 and 4 categories, Sullivan et al. (2006) 10 categories, and the OYS 8 and 20 categories. All these differences limit the comparability of mean diversity index levels across the four studies.

Moving on to the second main conclusion, the findings from the current study were less robust across both analytical approaches. When the predictive effects of three relevant correlates were controlled for each other in multivariate analyses, results of the aggregate-level analyses indicated consistently across all official records and self-report measures that just one of the correlates, namely the total count of offenses, was significantly associated with engagement in violent crime. Similar findings were reported for the Cambridge Study (Piquero et al., 2007). In contrast, differing correlates emerged in the individual-level analysis as significant predictors of offender versatility as a function of the crime measure at hand. Overall, these results are not fully consistent with Patterson's coercion model which would have expected that the same correlates are related to both engagement in violent crime and versatile offending.

Interestingly, our individual-level findings on the correlates of official records measures were fairly consistent with those of prior studies in which onset ages of offending and/or offense frequency emerged as fairly robust correlates of diversity index levels (Mazerolle et al., 2000; McGloin et al., 2007; Sullivan et al., 2006), although this was not always the case (Piquero et al., 1999). The relation of gang association with each of the indices of crime points to the importance of these deviant associations in crime and crime outcomes. In contrast, our individual-level results on the correlates of the self-report measure were largely inconsistent with existing scant research. To the best of our knowledge, only McGloin et al. (2007) and Sullivan et al. (2006) analyzed correlates of self-report diversity index levels. Both studies were based on a sample of incarcerated offenders from Nebraska and focused on offender versatility in the past 36-month period. It is likely that time-aggregation effects and sample characteristics account for the different findings between the OYS-men and the Nebraska study.

Some caveats are warranted in interpreting the findings from this study. First, Sullivan et al. (2006) showed that time-aggregation effects may occur in analyses of diversity indexes; that is, studies spanning longer time periods will likely yield higher estimates of offender versatility. Such effects may also be relevant for the evaluation of correlates of offender versatility. Second, analyses were conducted with a relatively small community sample of at-risk men who were predominantly White. Thus, findings from this study may not generalize to female offenders, offenders from different ethnic/racial groups, or offenders from high-risk or incarcerated populations. The extension of this line of research to these groups continues to be important. Third, the self-report data for the OYS men captured a slightly shorter time span than the official records data (self-report measures of offending were not administered during Waves 1–3). However, considering the unusually long time

period that was assessed in the current study, it appears unlikely that this difference influenced the key findings in a clearly discernible way.

Fourth, the diversity index was calculated with 20 crime categories for the official records measures but only 8 categories for the self-report measure. This was not ideal because it might have affected the distributions of the diversity index for official records versus self-report measures of crime. Although our results revealed robust evidence for versatility of offending across all diversity indexes (regardless of data source), it is possible that the different diversity index distributions contributed to the different sets of correlates that were found for official records versus self-report diversity indexes. Fifth, as is the case for virtually all individual-level measures of offender specialization, the diversity index has some inherent limitations, such as the potential confound with the frequency of offending and the fact that it does not provide information on the form of specialization (e.g., Sullivan et al., 2009). Although some of these problems are alleviated by more recently applied individual-level approaches (e.g., the method proposed by Nieuwebeerta et al., 2011), these newer approaches are subject to their own set of limitations and no consensus exists about the best way to conceptualize and measure offender specialization (Nieuwebeerta et al., 2011; Sullivan et al., 2009; Sullivan & McGloin, 2014). In addition, the diversity index, which continues to be used in recent work (e.g., McGloin et al., 2007; Sullivan et al., 2009), appeared to be the best choice for the current study for the reasons described earlier.

Sixth, the examination of correlates of offender specialization at the aggregate-level analysis focused on predicting engagement in violent crime, similar to the approach taken by Piquero et al. (2007). Alternative approaches, including the method proposed by DeLisi et al. (2011), provide a more direct way to explain specialization in violent offending. However, as stated above, our approach was justifiable given the theoretical framework and absence of detectable specialization in violent crime at the aggregate-level analysis. Seventh, our measure of early onset of offending was based on a subjective classification approach (Patterson & Yoerger, 1993; 1997) that has been used in many prior studies with the OYS. Alternatively, measures derived from objective classification approaches could have been used for the OYS (e.g., Wiesner & Capaldi, 2003; Wiesner, Capaldi, & Kim, 2007). Both classification approaches have their own strengths and limitations (e.g., Nagin & Tremblay, 2005).

Nevertheless, this study had unique strengths, notably the availability of self-report and official records measures of crime across a 23-year time span which almost no other study can match, and produced robust evidence of offender versatility rather than specialization in the crimes they commit. Further research should seek to cross-validate the findings from this study, ideally with larger samples over even longer observation periods. Such research should consider broader sets of predictor variables, including time-invariant and/or time-varying measures of local life circumstances (McGloin et al., 2007; Sullivan et al., 2006). This will be especially important for studies aiming to test competing theoretical explanations of offender versatility, which was not a goal of this study.

Acknowledgments

Author Notes

Support for the Oregon Youth Study was provided by Grant R37 MH 37940 from the Prevention, Early Intervention, and Epidemiology Branch, National Institute of Mental Health (NIMH), U. S. Public Health Service (PHS). Support for the Couples Study was provided by Grant HD 46364 from the National Institute of Child Health and Human Development (NICHD) and National Institute on Drug Abuse (NIDA), U.S. PHS. We thank Jane Wilson, Rhody Hinks, and the Oregon Youth Study team for high quality data collection, Alicia Miao for analysis assistance, and Sally Schwader for editorial assistance with the manuscript.

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Table 1.
Probability of Violent Offending across a 23-Year Span for Official Arrests (N=206)

1 Number of Offenses Committed	2 Observed Number of Offenders	3 Observed Number of Nonviolent Offenders	4 Observed Number of Violent Offenders	5 Observed Number of Violent Offenses	6 Observed Number of All Offenses	7 Expected Number of Nonviolent Offenders	8 Expected Nonviolent Percentage	9 Expected Number of Violent Offenders	10 Expected Violent Percentage	11 Test-Statistic (df)
1	37	33	4	4	37	33.31	90.02	3.69	9.98	$\chi^2(1)=0.03$
2	19	16	3	4	38	15.40	81.03	3.60	18.97	$\chi^2(1)=0.10$
3	17	13	4	4	51	12.40	72.94	4.60	27.06	$\chi^2(1)=0.08$
4	6	5	1	1	24	3.94	65.66	2.06	34.34	$\chi^2(1)=0.55$
5	4	2	2	2	20	2.36	59.10	1.64	40.90	$\chi^2(1)=0.08$
6	4	2	2	4	24	2.13	53.20	1.87	46.80	$\chi^2(1)=0.01$
7	3	2	1	1	21	1.44	47.89	1.56	52.11	$\chi^2(1)=0.20$
8	4	1	3	4	32	1.72	43.11	2.28	56.89	$\chi^2(1)=0.23$
9	5	1	4	10	45	1.94	38.81	3.06	61.19	$\chi^2(1)=0.29$
10	4	0	4	7	40	1.40	34.93	2.60	65.07	$\chi^2(1)=0.75$
11	4	2	2	4	44	1.26	31.45	2.74	68.55	$\chi^2(1)=0.20$
12	4	1	3	8	48	1.13	28.31	2.87	71.69	$\chi^2(1)=0.01$
13	1	1	0	0	13	0.25	25.48	0.75	74.52	$\chi^2(1)=0.75$
14	5	3	2	2	70	1.15	22.94	3.85	77.06	$\chi^2(1)=0.89$
15	4	0	4	8	60	0.83	20.65	3.17	79.35	$\chi^2(1)=0.21$
16	1	0	1	2	16	0.19	18.59	0.81	81.41	$\chi^2(1)=0.04$
17	4	1	3	8	68	0.67	16.73	3.33	83.27	$\chi^2(1)=0.03$
18	3	0	3	7	54	0.45	15.06	2.55	84.94	$\chi^2(1)=0.08$
19	1	0	1	2	19	0.14	13.56	0.86	86.44	$\chi^2(1)=0.02$
20	4	0	4	7	80	0.49	12.20	3.51	87.80	$\chi^2(1)=0.07$
21	1	0	1	1	21	0.11	10.99	0.89	89.01	$\chi^2(1)=0.01$
24	3	0	3	9	72	0.30	9.89	2.70	90.11	$\chi^2(1)=0.03$
25	1	0	1	4	25	0.09	8.90	0.91	91.10	$\chi^2(1)=0.01$
26	2	1	1	1	52	0.16	8.01	1.84	91.99	$\chi^2(1)=0.38$

1 Number of Offenses Committed	2 Observed Number of Offenders	3 Observed Number of Nonviolent Offenders	4 Observed Number of Violent Offenders	5 Observed Number of Violent Offenses	6 Observed Number of All Offenses	7 Expected Number of Nonviolent Offenders	8 Expected Nonviolent Percentage	9 Expected Number of Violent Offenders	10 Expected Violent Percentage	11 Test-Statistic (df)
27	1	0	1	1	27	0.07	7.21	0.93	92.79	$\chi^2(1)=0.01$
31	1	0	1	1	31	0.06	6.49	0.94	93.51	$\chi^2(1)=0.00$
34	2	0	2	3	68	0.12	5.84	1.88	94.16	$\chi^2(1)=0.01$
40	1	0	1	4	40	0.05	5.26	0.95	94.74	$\chi^2(1)=0.00$
42	1	0	1	5	42	0.05	4.74	0.95	95.26	$\chi^2(1)=0.00$
Total	147	84	63	118	1182	83.59	56.86	63.41	43.14	$\chi^2(28)=5.08$

Note. Robbery counted as violent offense. Fraction of arrests for violent offenses = 118/1182 = 0.0998. Fraction of arrests for nonviolent offenses = 1064/1182 = 0.9002. No individual was arrested for 22, 23, 28, 29, 30, 32–33, 35–39, 41, or more than 42 offenses.

Table 2.
Probability of Violent Offending across a 20-Year Span for Self-Reported Delinquent Acts (N = 206)

1 Number of Offenses Committed	2 Observed Number of Offenders	3 Observed Number of Nonviolent Offenders	4 Observed Number of Violent Offenders	5 Observed Number of Violent Offenses	6 Observed Number of All Offenses	7 Expected Number of Nonviolent Offenders	8 Expected Nonviolent Percentage	9 Expected Number of Violent Offenders	10 Expected Violent Percentage	11 Test-Statistic (df)
1-5	5	2	3	3	12	4.06	81.11	0.94	18.89	$\chi^2(1)=4.47^*$
7-10	5	2	3	6	42	3.29	65.79	1.71	34.21	$\chi^2(1)=0.97$
11-15	6	1	5	36	82	3.20	53.36	2.80	46.64	$\chi^2(1)=1.73$
17-24	6	1	5	75	131	2.60	43.28	3.40	56.72	$\chi^2(1)=0.75$
25-30	5	0	5	33	137	1.76	35.11	3.24	64.89	$\chi^2(1)=0.95$
31-35	6	2	4	63	199	1.71	28.48	4.29	71.52	$\chi^2(1)=0.02$
37-45	6	1	5	91	250	1.39	23.10	4.61	76.90	$\chi^2(1)=0.03$
54-58	5	2	3	28	278	0.94	18.73	4.06	81.27	$\chi^2(1)=0.28$
59-74	5	1	4	100	320	0.76	15.20	4.24	84.80	$\chi^2(1)=0.01$
82-95	5	1	4	35	443	0.62	12.32	4.38	87.68	$\chi^2(1)=0.03$
96-101	5	2	3	120	494	0.50	10.00	4.50	90.00	$\chi^2(1)=0.50$
107-117	5	1	4	16	567	0.41	8.11	4.59	91.89	$\chi^2(1)=0.08$
118-127	5	0	5	201	608	0.33	6.58	4.67	93.42	$\chi^2(1)=0.02$
132-161	6	0	6	296	883	0.32	5.33	5.68	94.67	$\chi^2(1)=0.02$
162-184	5	0	5	198	864	0.22	4.33	4.78	95.67	$\chi^2(1)=0.01$
187-209	5	0	5	245	978	0.18	3.51	4.82	96.49	$\chi^2(1)=0.01$
218-229	5	0	5	128	1118	0.14	2.85	4.86	97.15	$\chi^2(1)=0.00$
246-275	5	0	5	451	1330	0.12	2.31	4.88	97.69	$\chi^2(1)=0.00$
278-311	5	0	5	385	1476	0.09	1.87	4.91	98.13	$\chi^2(1)=0.00$
316-335	5	0	5	567	1620	0.77	1.52	4.92	98.48	$\chi^2(1)=0.00$
337-367	5	1	4	882	1761	0.06	1.23	4.94	98.77	$\chi^2(1)=0.18$
378-428	5	1	4	584	1992	0.05	1.00	4.95	99.00	$\chi^2(1)=0.18$
443-460	5	0	5	535	2258	0.04	0.81	4.96	99.19	$\chi^2(1)=0.00$
464-491	5	0	5	633	2392	0.03	0.66	4.97	99.34	$\chi^2(1)=0.00$
494-539	5	0	5	626	2601	0.03	0.53	4.97	99.47	$\chi^2(1)=0.00$

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1 Number of Offenses Committed	2 Observed Number of Offenders	3 Observed Number of Nonviolent Offenders	4 Observed Number of Violent Offenders	5 Observed Number of Violent Offenses	6 Observed Number of All Offenses	7 Expected Number of Nonviolent Offenders	8 Expected Nonviolent Percentage	9 Expected Number of Violent Offenders	10 Expected Violent Percentage	11 Test-Statistic (df)
550–592	5	0	5	168	2864	0.02	0.43	4.98	99.57	$\chi^2(1)=0.00$
609–681	5	0	5	669	3170	0.02	0.35	4.98	99.65	$\chi^2(1)=0.00$
688–760	6	0	6	387	4283	0.02	0.28	5.98	99.72	$\chi^2(1)=0.00$
781–871	5	0	5	991	4126	0.01	0.23	4.99	99.77	$\chi^2(1)=0.00$
943–1076	5	0	5	1165	4962	0.01	0.19	4.99	99.81	$\chi^2(1)=0.00$
1105–1184	5	0	5	2070	5682	0.01	0.15	4.99	99.85	$\chi^2(1)=0.00$
1209–1275	5	0	5	839	6230	0.01	0.12	4.99	99.88	$\chi^2(1)=0.00$
1277–1385	5	0	5	1246	6656	0.01	0.10	5.00	99.90	$\chi^2(1)=0.00$
1399–1713	5	0	5	2071	7617	0.00	0.08	5.00	99.92	$\chi^2(1)=0.00$
1821–2254	5	0	5	2682	10421	0.00	0.01	5.00	99.93	$\chi^2(1)=0.00$
2313–2703	5	0	5	3733	12030	0.00	0.00	5.00	99.95	$\chi^2(1)=0.00$
2709–3535	5	0	5	4077	14924	0.00	0.00	5.00	99.96	$\chi^2(1)=0.00$
3591–4156	5	0	5	3049	19994	0.00	0.00	5.00	99.96	$\chi^2(1)=0.00$
4297–4797	5	0	5	1818	22943	0.00	0.00	5.00	99.97	$\chi^2(1)=0.00$
5573–9199	4	0	4	2066	27912	0.00	0.00	4.00	99.98	$\chi^2(1)=0.00$
Total	205	18	187	33368	176650	23.00	11.22	182.00	88.78	$\chi^2(39)=10.26$

Note. Robbery counted as violent offense. Fraction of self-reported violent offenses = 33386/176650 = 0.1889. Fraction of self-reported nonviolent offenses = 143282/176650 = 0.8111.

* $p < .05$

Table 3.

Logistic Regression Analyses Predicting Engagement in Violent Crime (N = 206)

Variable	Single-Predictor Regression Models	Multivariate Regression Models		
	<i>B</i>	<i>B</i>	<i>SE</i>	<i>Exp(B)</i>
<i>Prediction for Official Arrests</i>				
Total Count Arrests	0.27 ***	0.26 ***	0.05	1.30
Early Onset	2.10 ***	0.35	0.50	1.42
Total Count Gang Association	0.38 ***	0.02	0.12	1.02
Constant	--	-2.50 ***	0.31	--
Model Chi-Square (<i>df</i>)	--	102.41 (3) ***		
<i>Prediction for Official Convictions</i>				
Total Count Convictions	0.25 ***	0.19 ***	0.05	1.21
Early Onset	1.91 ***	0.74	0.50	2.10
Total Count Gang Association	0.34 ***	0.17	0.10	1.19
Constant	--	-2.94 ***	0.35	--
Model Chi-Square (<i>df</i>)	--	49.96 (3) ***		
<i>Prediction for Self-Reported Delinquent Acts</i>				
Total Count Delinquent Acts	0.01 ***	0.01 **	0.00	1.01
Early Onset	1.67 *	1.18	0.82	3.27
Total Count Gang Association	1.22 *	1.04	0.53	2.83
Constant	--	-0.18	0.35	--
Model Chi-Square (<i>df</i>)	--	55.07 (3) ***		

Note. Early onset of offending was coded as 1 (Yes) versus 0 (No early arrest). For Official Arrests and Convictions, Engagement in Violent Crime was coded as 1 (Yes) versus 0 (No). For Self-Reported Delinquent Acts, Violent Crime was coded as 1 (2 or more acts) versus 0 (0 or 1 act).

***
 $p < .001$.

**
 $p < .01$.

*
 $p < .05$.

Table 4.

Tobit Regression Analyses Predicting Three Diversity (D) Index Measures

Parameter	D Official Arrests			D Official Convictions			D Self-Reports Delinquency		
	Single Predictor	Multivariate Predictors	SE	Single Predictor	Multivariate Predictors	SE	Single Predictor	Multivariate Predictors	SE
Constant	---	0.52 ***	0.02	---	0.47 ***	0.03	---	0.49 ***	0.02
Total Count of Offenses <i>I</i>	0.01 ***	0.01 ***	0.00	0.02 ***	0.01 ***	0.00	0.00	-0.00	0.00
Early Onset before Age 14	0.14 ***	0.05	0.03	0.14 ***	0.08 *	0.04	0.04	0.02	0.04
Total Count Gang Association	0.03 ***	0.02 **	0.01	0.03 **	0.02 *	0.01	0.02 **	0.03 **	0.01
Sigma (σ)	---	0.15 ***	0.01	---	0.15 ***	0.01	---	0.21 ***	0.01
Model LL	---	40.83		---	31.04		---	26.97	

Note. Parameter estimates (*b*) are unstandardized Tobit regression coefficients.

I. Total count of official arrests for Tobit regression model predicting *D* Official Arrests; total count of official convictions for Tobit regression model predicting *D* Official Convictions; total count of self-reported delinquent acts for Tobit regression model predicting *D* Self-Reports.

***
 $p < .001$.**
 $p < .01$.*
 $p < .05$.