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# Arrest Trajectories Across a 17-Year Span for Young Men: Relation to Dual Taxonomies and Self-Reported Offense Trajectories

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## Abstract

The purpose of this study was to evaluate the impact of different operationalizations of offending behavior on the identified trajectories of offending, and to relate findings to hypothesized dual taxonomy models. Prior research with 203 young men from the Oregon Youth Study identified six offender pathways, based on self-report data (Wiesner and Capaldi, 2003). The present study used official records data (number of arrests) for the same sample. Semiparametric group-based modeling indicated three distinctive arrest trajectories: high-level chronics, low-level chronics, and rare offenders. Both chronic arrest trajectory groups were characterized by relatively equal rates of early onset offenders, thus indicating some divergence from hypothesized dual taxonomies. Overall, this study demonstrated limited convergence of trajectory findings across official records versus self-report measures of offending behavior.

### Keywords

Offending; Trajectories; Life Span

Characterization of offending careers remains a major goal in criminological research. In recent years, the maturation of long-term longitudinal studies, along with advances in statistical approaches to modeling developmental trajectories, has resulted in important progress in such characterization. Several studies utilizing finite mixture modeling techniques have demonstrated considerable heterogeneity in developmental pathways of self-reported offending behavior across the adolescent and young adult years (for an overview, see Piquero, 2005). However, a number of important questions remain to be addressed regarding heterogeneity in criminal careers. First, the extent to which trajectory groupings identified through self-reports may relate to groupings identified by official records is not known. Second, the extent to which key features of arrest trajectories identified by mixture modeling techniques will relate to the dual taxonomies, which have been the predominant models of offending careers for over a decade (e.g., Moffitt, 1993, 1997; Patterson and Yoerger, 1993, 1997), is

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relatively understudied. The purpose of the present study was to address these questions for young men in the Oregon Youth Study (OYS) for whom arrest records were available from ages 10–11 to 26–27 years and for whom criminal career groupings were already examined using self-reported criminal activity (Wiesner and Capaldi, 2003).

With few exceptions (e.g., McDermott and Nagin, 2001), studies using mixture modeling approaches have indicated three or more delinquency pathways in addition to a nonoffender group (e.g., Blokland, Nagin, and Nieuwbeerta, 2005; Chung, Hill, Hawkins, Gilchrist, and Nagin, 2002; D'Unger, Land, McCall, and Nagin, 1998; Fergusson, Horwood, and Nagin, 2000; Laub, Nagin, and Sampson, 1998; Nagin, Farrington, and Moffitt, 1995; White, Bates, and Buyske, 2001; Wiesner and Capaldi, 2003). Most studies found both a high-level chronic and a low-level chronic offender trajectory group. A few studies also identified adult-onset pathways or escalating patterns of offending behavior (e.g., Chung et al., 2002; D'Unger et al., 1998; White et al., 2001). On the basis of the accumulated evidence so far, the existing dual taxonomies of antisocial and criminal behavior across the life-course (e.g., Moffitt, 1993, 1997; Patterson, 1996; Patterson and Yoerger, 1993, 1997) need revision and extension, including the addition of a third pathway of chronic low-level offenders.

Although there is a fair degree of consistency across a wide range of samples with respect to both the number of groups and the shapes of offender trajectories, it is also clear that substantive findings are affected by a variety of factors, including the length and intervals of follow-up, age range, chosen measures, incarceration times, and sample characteristics (Piquero, 2005; Wiesner and Capaldi, 2003). Prior studies have rarely addressed whether patterns of identified developmental pathways of offending converge across different measures of offending behavior, in particular self-reports as opposed to official records. During a reanalysis of data from the Cambridge Study, Nagin et al. (1995) discovered that adolescence-limited offenders continued to offend according to their self-reports, although they had appeared to desist from offending based on their official records. This discrepancy indicates some limits to convergence between self-reports and official records data for at least some offender pathways. Moreover, it has been suggested that the greater amount of information available in self-report data (i.e., higher frequencies) allows for a better partitioning of offenders into more distinctive trajectory groups; thus, the identification of more and better specified trajectory groups compared to studies based on official records (Piquero, 2005).

## Self-Reports versus Official Records

Self-report and official records measures of offending behavior each have specific strengths and weaknesses. Official records may include more of the worst offenses and are an objective measure with accurate recording of age at offense; however, they capture only a small fraction of the true number of offenses committed. Many crimes go undetected by the police, some offenders do not get caught, and some crimes are not accurately recorded by the authorities. On the other hand, self-report measures are affected by a variety of biases, including memory and concealment problems, but capture a larger fraction of the true number of offenses committed (Farrington et al., 2003; Farrington, Loeber, Stouthamer-Loeber, van Kammen, and Schmidt, 1996; Huizinga and Elliott, 1986; Lauritsen, 1998; Maxfield, Weiler, and Widom, 2000). The ratio of police contacts to self-reported offenses has been estimated at around 3–10:100 (Elliott and Voss, 1974; Gold, 1966). Therefore, self-report measures and official records provide two alternative views on offending behavior (Farrington et al., 2003), which will be related to different empirical findings.

Because official arrest rates reflect the "tip of the iceberg" and provide a rather conservative estimate of the actual amount of criminal activity, it is unlikely that mixture modeling of arrests will result in as many pathway groups as is the case with self-report data (see Piquero, 2005).

Six pathways of offending behavior were identified utilizing self-report offending for the OYS from late childhood to ages 23–24 years via mixture modeling: chronic high-level, chronic low-level, decreasing high-level, decreasing low-level, rare, and nonoffenders (Wiesner and Capaldi, 2003). The pathways are displayed in Figure 1.Consequently, we expected that a minimum of three but less than six trajectory groups would be identified for officially recorded offending behavior for this sample. On the basis of prior empirical trajectory work and existing dual taxonomies of offending (e.g., Moffitt, 1993, 1997; Patterson, 1996; Patterson and Yoerger, 1993, 1997), we further predicted that the majority of the sample would belong to a rare or nonoffender arrest trajectory group, with the rest belonging to, at least, a high-level chronic group and possibly a second low-level chronic group. Given the age span covered by the present study and the previous findings with no escalating trajectory (Wiesner and Capaldi, 2003), we did not expect to find an escalating pattern of offending.

## Characteristics of Arrest Trajectories

A second goal of the present study was to examine key aspects of the identified arrest trajectory groups and to relate them to expectations derived from early taxonomy theories, particularly pertaining to ages of onset and to associations with severity of offending.According to dual taxonomies (e.g., Moffitt, 1993, 1997; Patterson, 1996; Patterson and Yoerger, 1993, 1997), life-course persistent or early-onset offenders are characterized by early initiation of and more severe and chronic offending behavior, and are a relatively small group of offenders. By comparison, late onset or adolescence-limited offenders are posited to be a relatively larger group of youth who initiate offending relatively later in life and to show less severe and chronic offending, remaining involved in offending for a relatively shorter time period. On the basis of these theories and other evidence of offending patterns (Piquero, 2005), we hypothesized that any high-level chronic arrest trajectory group would contain a relatively high proportion of young men with both an early onset (first arrest prior to age 14 years) and a history of more severe offending behavior (as indexed by the lifetime frequencies of arrests and on being arrested for one or more *violent* crimes) compared to other arrest trajectory groups, especially rare and nonoffenders. Prior evidence from self-reports data (Wiesner and Capaldi, 2003) also suggested expected findings that would not fit the early taxonomies, particularly the characterizations in the Moffitt taxonomy of life-course persistence versus adolescent limited (no group with a clear adolescent onset and a decrease in the late adolescent years was found for self-report data in the OYS). We expected that the highest level and chronic arrest trajectory would show some decrease in offending in early adulthood and that the less severe offenders would also show some decrease, but that their offending behavior would continue and not be strictly limited to adolescence.

Finally, we expected some association between self-report and official records pathway groups. Congruence between chronic offenders identified in court referrals and chronic offenders identified in self-reports has been found, such that to a considerable extent self-reports and court referrals identified the same individuals as the worst offenders (Farrington et al., 2003). A similar pattern of overlap was also reported in a study from Fergusson et al. (2000). It is not clear whether these findings also apply to more long-term data on offending, especially differing trajectories of offending from childhood through the early adult years, and to other official records measures of offending (e.g., number of arrests by the police). On the basis of these findings, we expected that an increased proportion of members of any chronic arrest trajectory group would also belong to the chronic high-level self-report offender group. At the same time, we also expected to find chronic self-reported offenders among the rare or nonoffender arrest trajectory members, possibly depicting the most successful offenders (i.e., those who did not get caught by the police). Due to the limited empirical literature, we did not formulate specific hypotheses for other trajectory groups.

Summarizing, the present study used data from an at-risk sample of young men to identify the number of distinctive offender pathways, based on official records data (number of arrests) and spanning the period from childhood through early adult years, and to examine key features of the identified trajectory groups (e.g., age of onset of offending).

# METHOD

## Sample

The analyses were conducted using data from the OYS, an ongoing multiagent and 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 when compared to others in the same region. Of the eligible families, 206 agreed to participate (a 74.4% participation rate). The OYS consists of two successive Grade 4 (ages 9–10 years) cohorts of 102 and 104 boys, recruited in 1983–84 and 1984–85 (for details see Capaldi and Patterson, 1987). The average retention rate was 98% through the early 20s and 94% of living participants still remained as part of the panel in Year 20. Participants who moved were retained in the study, with interviewers traveling to assess them. The two cohorts had very similar demographic characteristics and were combined for the current analyses. The sample was predominantly Caucasian (90%), 75% lower or working class, and over 20% received some form of unemployment or welfare assistance in the first year of the study, a recession year for the local economy (Patterson, Reid, and Dishion, 1992). Three young men who died during the study period were excluded from the analyses. Hence, the final sample size was 203.

## Procedures

Assessment on the OYS was yearly, multimethod, and multiagent, including in-person interviews and questionnaires for self and parents at the 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 records data), and court records data. Family consent was mandatory. Participants were paid at each assessment wave.

## Measures

**Official arrests—**Juvenile or adult court record searches were conducted locally for the study boys each year from ages 10–11 to 26–27 years (i.e., Waves 2 to 18). 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. Arrests for minor traffic violations or contempt of court were excluded from the total arrest counts. Fifty-nine (29.1%) of the young men were never arrested during this time period, and 144 (70.9%) were arrested at least once (range 1–39, mean= 6.97, mode = 1, median = 3, 3$^{rd}$ Quartile= 11). Out of the total number of arrests 17.7% were for felony theft, 15.4% for misdemeanor theft, 7.9% for misdemeanor violence, 3.2% for felony violence, 3.8% for misdemeanor substance use, and 2.9% for felony substance use offenses.

**Exposure time—**Data on exposure times were obtained from court records as well as parental reports and boy’s self-reports on living circumstances. Within each year time period, participants were coded free for the number of weeks that they were not serving time in jail, prison, or a juvenile detention and correction center; otherwise, they were coded as being under some form of correctional supervision. For example, a participant who was in prison for 15 weeks during a particular year would be coded as having exposure time equal to 37 weeks for that annual time period.

**Trajectories of Self-Reported Offending—**The identification and characteristics of differing pathways of self-reported offending behavior for the OYS were described in an earlier report (see Wiesner & Capaldi, 2003). The measure of self-reported offending behavior was identical across assessment waves. Systematic collection of self-report data on offending behavior of the study boys began at ages 12 to 13 years (OYS Year 4). At each assessment year, study participants filled out the Elliott Delinquency Scale (Elliott, Ageton, Huizinga, Knowles and 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 offending behavior in the past year was formed by summing up the open-ended responses across 30 items (20 nonindex and 10 index offenses) for each wave. The selected 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, purposely damaged property of others, stole a motor vehicle). None of the selected items included status offenses or traffic violations. Overall, the highest frequencies were reported for relatively less severe offenses by the young men (e.g., hit someone else, sold marijuana, damaged other property, stole something worth less than $5).

Using latent growth mixture modeling (Muthén and Muthén, 2000; Muthén and Shedden, 1999), Wiesner and Capaldi (2003) identified homogeneous subgroups with distinctive developmental trajectories of self-reported offending behavior from ages 12–13 to 23–24 years. A detailed account of the method, analysis strategy, model selection criteria, and model fit statistics is given in their study. Briefly summarizing, statistical analysis suggested that a six-class model fitted the data best. The trajectory groups included 32 (15.7%) *chronic high-level offenders*, 38 (18.6%) *chronic low-level offenders*, 57 (27.9%) *decreasing high-level offenders*, 44 (21.6%) *decreasing low-level offenders*, 23 (11.3%) *rare offenders*, and 10 (4.9%) *nonoffenders*. The classification quality was quite good, as indicated by average posterior class probabilities ranging from .83 to 1.00. The fitted and observed growth curves are displayed in Figure 1.

**Early Starter/Late Starter Classification (from Patterson and Yoerger, 1993, 1997)—***Early starters* encompassed those with first arrest before age 14 years (25.6%, $n$ = 52), *late starters* those with first arrest between age 14 and 17.99 years (28.6%, $n$ = 58). In addition, *adult starters* were defined as those with first arrest at age 18 years or later (17.2%, $n$ = 35). *Nonoffenders* had no history of arrests through ages 26–27 years (28.6%, $n$ = 58).

The differing measures of offending behavior just described have been used in several prior studies with the OYS. For more general information and basic descriptive findings on these measures, the interested reader is referred elsewhere (e.g., Patterson and Yoerger, 1993; Wiesner and Capaldi, 2003; Wiesner, Kim, and Capaldi, 2005).

**Analytic Plan—**Unobserved heterogeneity in trajectories of officially recorded offending behavior was modeled utilizing semiparametric group-based modeling (SGM). SGM is available through a customized SAS macro developed by Nagin and colleagues (Jones and Nagin, 2005; Jones, Nagin, and Roeder, 2001; Nagin, 1999, 2005; Nagin and Tremblay, 2001). In contrast to more conventional methods for analyzing developmental trajectories, most prominently hierarchical modeling (e.g., Bryk and Raudenbush, 1992; Goldstein, 1995) and latent growth curve modeling (e.g., McArdle and Epstein, 1987; Willett and Sayer, 1994), the SGM approach assumes that the given population is composed of a mixture of distinct (but unobserved) subgroups, each defined by a prototypical growth curve. More specifically, a continuous distribution is approximated from a discrete mixture (Nagin, 1999, 2005; Nagin and Tremblay, 2001). SGM is especially well suited for the present study because it allows for cross-group differences in the shapes of distinctive developmental trajectories of the phenomena under investigation and fits semiparametric (discrete) mixtures of various distributions to longitudinal data. SGM can accommodate (un)censored normal, count, or binary data. Model parameters are estimated with a maximum likelihood estimator that allows for missing values in the longitudinal data. Thus, SGM makes full use of available data and does not lose information through listwise deletion of cases (Jones et al., 2001). To avoid local minima and ensure the stability of trajectory-class solutions, it is critical to specify start values and to repeatedly estimate models using different sets of start values (see Hipp and Bauer, 2006; Jones et al., 2001). A model is considered stable when similar solutions are obtained with different sets of start values.

Model selection requires determination of the number of groups that best describes the data. In SGM, a $k$ group model is not nested within a $k + 1$ group model; therefore, it is not appropriate to use the likelihood ratio test for model selection. Instead, the Bayesian Information Criterion (BIC) is used as a basis for selecting the optimal model because it can be used for comparison of both nested and unnested models (Kass and Raftery, 1995; Raftery, 1995). Generally, the model with the smallest absolute BIC value is chosen. Note that the BIC criterion tends to favor models with fewer groups because it rewards parsimony. Additional model selection criteria include the Akaike Information Criterion (AIC)[1] and the BIC log Bayes factor approximation, $2\ log_e\ (B_{10})$. It is calculated as ($BIC_{k+1} - BIC_k$) *2, where the difference in BIC scores is the BIC of the alternative, more complex, model minus the BIC of the null, simpler, model. The log form of the Bayes factor is interpreted as the degree of evidence favoring the alternative model (Jones et al., 2001). Analyses were conducted using PROC TRAJ (Version 2; Jones et al., 2001) with SAS 9.1.

# RESULTS

## Descriptives

As a starting point, the relationship between self-reported and officially recorded offending behavior was described in a more basic way for the whole sample, similar to prior research (e.g., Brame, Fagan, Piquero, Schubert and Steinberg, 2004; Cohen, 1986; Dunford and Elliott, 1984). Table 1 shows the arrest activity of the young men conditional on levels of self-reported offending behavior. When conditioning the rate of arrest for any type of offense on the number of total self-reported offenses (i.e., index plus nonindex offenses; see top portion of Table 1), it can be seen that it increased from 20% for those young men without self-reported engagement in offending to 80% for those who reported 201 or more offenses during the given time period. A similar trend was observed for the mean number of arrests.

This was also found when the focus was limited to serious offending behavior. Specifically, the rate of arrest for any type of offense was conditioned on the number of self-reported index[2] offenses (see bottom portion of Table 1) in order to determine if those reporting involvement in more serious crimes were arrested at a higher rate. Although the arrest data were not limited to arrests for index offenses, the results suggest that self-reported serious offenders indeed were arrested at a heightened rate. For example, 100% of the young men who reported 51 or more index offenses during the given time period were arrested at least once for any type of offense.

[1]Note that multiplying the reported BIC and AIC values with -2 yields the BIC and AIC statistic values compatible with other statistical software programs (e.g., *Mplus*).

[2]The following ten items were included in the count of self-reported index offenses: Used force or threat of force to rob person/store/bank, burglarized residence/building/business, broken or tried to break into building/vehicle to steal or look, used force or strong-armed methods to get money or things from people, had or tried to have sex with someone against their will, involved in gang fights, attacked someone with the idea to seriously hurt him, set or tried to set fire to building/car/other property, stole or tried to steal something worth more than $50, stole or tried to steal a motor vehicle.

### Identification of Distinctive Arrest Trajectories

Next, the SGM approach was used to identify subgroups with distinctive developmental trajectories of officially recorded offending behavior (i.e., number of arrests) from ages 10–11 through 26–27 years. The trajectories were modeled using the zero-inflated Poisson (ZIP) model. This model is particularly useful for modeling the conditional distribution of count data given group membership when there are more zeros than expected under the Poisson assumption (Lambert, 1992). This is common in antisocial and abnormal behavior that is typically concentrated in a small fraction of a given sample. Specifically, the model takes into account that individuals may enter periods of dormancy during which the probability of criminal activity is strictly zero. This zero-inflation parameter, or intermittency parameter, may or may not change with age (for some individuals, the dormancy period may last their whole life). During periods of activity, a Poisson model is used to describe the probability distribution of the number of times that a young man was arrested. A more detailed description of the ZIP model can be found in Roeder, Lynch, and Nagin (1999).

We tested one-, two-, and three-class models of arrest trajectories. Models with four, five, or six classes were also estimated, but failed to converge (i.e., leading to false convergence or unstable class solutions). Hence, the model search process stopped with a three-class model. Key features of the ZIP model included a cubic growth function, an intercept-only intermittency parameter (i.e., alpha equals 0) to account for dormancy periods, and the inclusion of incarceration information to control for exposure time on the street (i.e., number of weeks not under correctional supervision or in prison for a given year). If exposure time is not taken into account, the predicted rate of arrests could be underestimated and the shape of trajectories could be distorted, especially among high-level chronic offenders (Eggleston, Laub, and Sampson, 2004; Piquero et al., 2001). Alternative model specifications were tested in preliminary analyses, but did not result in improved model fit. The results of the final model series are summarized in Table 2.

On the basis of the BIC criterion, AIC criterion, and the BIC log Bayes factor approximation, the model with three classes was selected as the best-fitting model. The posterior probability of its being the correct model was 1.0, which indicates that the data fitted the model very well. Furthermore, the average and median posterior group membership probabilities for the three classes ranged from .926 to .998, which indicates a very good classification quality (see Nagin, 1999). Note that the SGM-approach assigns individuals to the trajectory group that best conforms to their observed behavior over time (i.e., the trajectory group for which their posterior probability of group membership is the highest). This procedure makes the assumption that the error in classification made when placing an individual into only one trajectory group based on the maximum posterior probability rule is small. In this study, the average and median posterior group membership probabilities were very high, and borderline individuals who had similar or equal probabilities across classes were extremely rare. Assignment uncertainty thus was not considered to be a problem for further analyses with this sample. Finally, the odds of correct classification were far greater than 5.0 for all three groups. The odds of correct classification is the ratio of the odds of correct classification into group *j* based on the maximum probability assignment rule and the odds of correct classification based on random assignment. The odds of correct classification values obtained for the three trajectory classes indicate that the final model had high assignment accuracy (see Nagin, 2005).

Figure 2 displays the observed and fitted trajectories for the three offender trajectory groups. The trajectory groups include rare offenders, low-level chronics, and high-level chronics.[3] The *rare offenders* (68.5%; with a 95% confidence interval of 61.7 to 75.3) consisted of 141 young men who almost never were arrested during the entire study period. The *low-level chronics* (22.3%; with a 95% confidence interval of 16.0 to 28.6) consisted of 43 young men who had a consistently low rate of arrests across the study period, with a slight peak around the middle adolescent years. The *high-level chronics* (9.2%; with a 95% confidence interval of 4.7 to 13.7) consisted of 19 young men who started with a similarly low arrest-rate, but then continuously increased toward a peak in the middle adolescent years, followed by a decrease to about the same level as the low-level chronic group in their early 20s and another increase around their mid twenties. Closer inspection revealed that this group contained a few young men with multiple arrests at the last two waves of assessment. Note that the young adult upsurge for this group was much less substantial when inspecting the observed rates of offending (see Figure 2). This indicates that the renewed increasing trend for this group should be interpreted with caution.

The 95% confidence intervals for the annual point estimates of the fitted trajectories generally did not overlap among the three groups (not shown). This indicates that the trajectories are distinct (Jones and Nagin, 2005). This was further substantiated by testing whether the trajectories were distinctive in the sense that they are not parallel, utilizing the Wald Test (Wald, 1943). The trajectories would be considered parallel ("linear gradation") if the intercept terms of the trajectories were significantly different but the coefficients of higher order terms of the polynomials describing the trajectories of the groups were not (Jones and Nagin, 2005). The Wald Test indicated that both the intercepts and the slope factor terms (i.e., linear, quadratic, cubic) were significantly different. The $\chi^2$ statistic for the intercept contrast was 7.57 ($df = 2$, $p < .05$), and the companion $\chi^2$ statistic for the equality of linear, quadratic, and cubic terms was 18.00 ($df = 6$, $p < .01$). This suggests that the three classes were well separated and characterized by nonparallel growth trajectories.

Because prior research has indicated that trajectory solutions can be affected by length of follow-up (Eggleston, Laub, and Sampson, 2004), SGM analyses of officially recorded offending behavior were next repeated for the time period from ages 12–13 through 23–24 years. This permitted a more direct comparison with the previous findings for self-reported offending and allowed to rule out length of follow-up as a potential explanation of differences in trajectory findings for self-report versus official-records measures of offending behavior. The model testing strategy was the same as the one described for the longer time-period and also included the estimation of various alternative model specifications. Briefly summarizing the results of this follow-up analysis, the trajectory solutions for official-records data on offending behavior proved to be remarkably stable across the two different time periods with regard to number of trajectory classes, proportions of identified classes, trajectory shapes, and classification quality. Hence, there is little evidence that differing length of follow-up influenced the findings of the present study in a major way.

## Characteristics of Arrest Trajectory Groups

Characteristics of the offense careers of the three arrest trajectory groups (based on the SGM analysis for the time period from ages 10–11 through 26–27 years) are depicted in Table 3, including numbers of arrests, arrests for violence, a cross-tabulation of arrest group by the six trajectory groups identified using self-reports, and ages at first arrest. The two chronic trajectory groups clearly differed from the rare-offender group in terms of severity, as indexed by the heightened rates of young men with multiple arrests as well as those with one or more violent arrests. Interestingly, proportions of men with multiple arrests were quite similar among the two chronic trajectory groups, although the high-level chronics contained a higher share

[3]The estimated growth factor means for the three trajectory classes were as follows: For the rare offenders, the intercept, linear, quadratic, and cubic factor means were -10.07 ($p < .001$), 13.27 ($p < .001$), −12.39 ($p < .01$), and 3.39 ($p < .01$). The low-level chronic offenders had intercept, linear, quadratic, and cubic factor means of −7.67 ($p < .001$), 12.92 ($p < .001$), −11.98 ($p < .001$), and 3.27 ($p < .001$). The means of the intercept, linear, quadratic, and cubic factor for the high-level chronic offenders were −6.60 ($p < .001$), 15.53 ($p < .001$), −17.46 ($p < .001$), and 5.68 ($p < .001$). The zero-inflated intermittency parameter for this model was estimated as −0.22 ($p < .05$).

of men with 10 or more arrests (94.7%) than did the low-level chronics (53.5%). This indicates that most members of both chronic arrest trajectory groups engaged in substantial amounts of criminal activity. Regarding arrests for a violent offense, very few men in the rare-offender grouping had such an arrest. Rather surprisingly, men in the low-level and the high-level chronic groupings had relatively similar proportions of men with two or more arrests for violent offences.

When the three arrest trajectory groups were cross tabulated with the six self-report offender pathway groups from Wiesner and Capaldi (2003), the pattern was fairly consistent with expectations. None of the high-level chronic arrestees and relatively few of the low-level chronics' were in the lowest three groupings according to self-reports (none, rare, and decreasing low-level offenders), and 57.9% of the high-level chronic arrest trajectory members were also members in the self-report chronic high-level offender pathway. As expected, the cross tabulation of the rare-offender arrest trajectory group with the six self-report offender pathways indicated that court records-based trajectory data underestimate delinquent activity to some degree. For instance, 5.7% of the rare-offender arrest trajectory group belonged to the self-report chronic high-level offender group. Figure 3 shows the average number of arrests for the six self-report offender pathway groups. Arrest rates were highest for the self-report chronic high-level offender group, with a peak in the adolescent years.

Finally, the cross-tabulation of the three arrest trajectories with Patterson's early starter/late starter classification (Patterson and Yoerger, 1993, 1997) revealed that contrary to expectation, the high-level chronic grouping contained very similar proportions of early starters to the low-level chronic group. As expected, both groups included relatively low rates of adult starters. Among the rare-offender group, about 40% of the men had no arrest during the study period, and the remainder were about equally likely to show adolescent onset (i.e., late starters) or adult onset, but in line with predictions were unlikely to show early onset. Overall there were a relatively large proportion of adult starters in the sample (17%) that was not predicted by either of the dual taxonomy theories.

## DISCUSSION

This study utilized an at-risk community sample of 203 young men, from ages 10–11 to 26–27 years, to examine distinctive developmental trajectories of offending as indexed by number of arrests, and the characteristics of these groupings of offenders. Using semiparametric group-based modeling (Nagin, 1999) and controlling for dormancy periods and exposure time, three trajectories of officially recorded offending behavior were identified: rare offenders (69%), low-level chronic offenders (22%), and high-level chronic offenders (9%). As expected, the majority of the young men belonged to the rare-offender group. The three groups were quite distinctive from each other and well separated.

The identification of three arrest trajectory groups in the present study stands in marked contrast to previous research from Wiesner and Capaldi (2003), which found six distinctive trajectories of offending based on annual assessments of self-reported delinquent behavior for the same sample. Hence, as expected and congruent with suggestions from Piquero (2005), fewer distinctive trajectory groups were found for officially recorded offending behavior compared to self-reported delinquent activity. Given the much higher rates of crime when assessed by self reports as opposed to official records, it was to be expected that greater heterogeneity might be discernible from self-reports, and thus that more trajectory groupings would be identified from self-reports compared with official records for the same men. Additional analyses revealed that this discrepancy between self-report versus official records trajectory findings did not result from the differences in length of follow-up (i.e., findings for the official record data were remarkably stable when the factor length of follow-up was held constant). However, this study is not in a position to completely rule out the alternative explanation that the discrepancy between self-report and official record trajectory findings was affected by usage of different statistical software programs (i.e., the self-report offending trajectory analysis was performed utilizing Mplus). Finite growth mixture modeling in SAS Proc Traj and Mplus differ in a number of ways. For instance, Mplus additionally allows for random effects within classes which permits testing a much broader set of model specifications but typically reduces the number of classes necessary to model heterogeneity in developmental trajectories relative to the more restrictive model imposed by SAS Proc Traj (Hipp and Bauer, 2006; Nagin and Tremblay, 2005). At the same time, Mplus does not offer the same flexibility as SAS Proc Traj to account for dormancy periods and exposure time, which was critical for adequate analysis of the official record data but much less so with the self-report data for the OYS (see Wiesner and Capaldi, 2003). Although it would have been preferable to hold the factor statistical software constant, we chose to utilize the software best suited for analysis of the given measure of offending behavior, recognizing that this would likely lead to an underestimation (rather than an overestimation) of the discrepancy in number of trajectory classes for self-report versus official record data of offending behavior within the present study.

Because of the lack of other comparable empirical research comparing empirically derived arrest trajectories and self-report trajectories for the same sample, replication of these findings with independent samples is critical, as well as extension to alternative official records measures of offending behavior (e.g., number of convictions, number of contacts with police). Further research might also pursue two additional avenues. First, this study basically applied an exploratory strategy (model searches were conducted to identify the number and shape of trajectory classes for each measure of offending behavior separately), whereas other studies could adopt a more confirmatory strategy in which the final model specification for one measure of offending behavior is cross-validated for the other measure. At a minimum, such work should focus on cross-validating the number of trajectories classes, whereas cross-validation of other model features such as shapes of trajectory groups or proportions of group membership may not always be a very realistic goal. For the OYS data, such a confirmatory approach was not a viable option because six-class trajectory models failed to achieve convergence for the official record data, and a cubic growth function proved to fit the official record data far better than the quadratic growth function from the self-reports analysis. In our view, the importance of adopting a confirmatory strategy must always be balanced with the distributional characteristics of the given measures of offending behavior. Second, it is critical to extend this line of research to an examination of the degree of convergence in risk factors and correlates of self-report versus official record based crime trajectories. Divergence in the number and/or shapes of trajectory classes across different measures of offending behavior may not always necessitate changes in prevention and intervention policy as long as the predictors of crime trajectories largely overlap across self-report and official record measures of offending.[4]

Prior studies have indicated that less than 10% of the population tend to be frequent and chronic offenders and account for a relatively large proportion of crimes, albeit with differing definitions of chronic as well as differing lengths of observations of careers. For example, in a classic study of delinquent careers, Wolfgang, Figlio and Sellin (1972) found that chronic offenders (those arrested five or more times by age 18 years) made up 6% of the Philadelphia 1945 cohort (and 18% of arrestees) but accounted for 52% of all arrests of cohort members. The relatively high prevalence of 9% as high level chronic offenders in the OYS sample, almost all of whom had 10 or more arrests by age 26–27 years, could be partially due to the at-risk nature of the OYS sample. The sample was at risk by virtue of living in neighborhoods with a

[4]We thank two anonymous reviewers for these excellent suggestions.

higher than usual incidence of delinquency for the medium-sized metropolitan area (which overall does not have a high crime rate). The majority of the sample was not showing higher levels of conduct problems at ages 9–10 years. Thus the relatively large proportion of men showing rather severe arrest histories in the sample was somewhat surprising – with almost all of the men in the High-Level Chronic grouping having 10 or more arrests, and almost all of the men in the Low-Level Chronic grouping having 5 or more arrests. The two groups totaled close to 1/3 of the sample. There are a number of factors which may relate to the relatively high arrest rates found in the current study. First, arrest practices change across historic periods, and from state to state, affecting arrest rates (Blumstein, Cohen, Roth, and Visher, 1986). Second, improvements in record keeping due to improved computer software and usage may have resulted in more accurate updating of arrest files in recent years. A very intensive record search procedure was used in the current study, with regular searches of juvenile and adult files, and searches of all areas where the study participant had lived. Finally, the study experienced both high recruitment and high retention rates, and thus may have retained more of the highly antisocial participants than usual.

The current analysis of official records data indicating three arrest trajectories showed some similarities to dual taxonomies of crime (e.g., Moffitt, 1993; Patterson and Yoerger, 1993). In particular, if the rare-offender group was considered predominantly a nonoffense group (over 70% of the group had 0 or 1 arrests), two trajectory groups were identified, one showing considerably more severe levels of offending than the other. However, these groups differed from the theorized groupings on some key features. Notably, both the high- and low-level chronic groupings contained relatively equal numbers of early onset youth, whereas both dual taxonomy models hypothesize that the less severe group starts later. Further differences included the fact that the arrests of the low-level chronic group, which was most analogous to the adolescent limited group in being less severe, were not limited to adolescence but continued into the twenties. The high chronic group showed the adolescent peak followed by decline hypothesized for the adolescent-limited group, although with an unexpected upsurge in the mid twenties. Laub and Sampson (2003) also found a pattern of peak offending at around 16 years of age followed by a steep decline for a sample of serious delinquents. They stated that "the … perhaps unexpected point is that the classic age-crime pattern (Hirschi and Gottfredson, 1983) is replicated even within a population that was selected for serious, persistent delinquent activity." (p. 86). The classic age pattern referred to involves a peak at around 16 years of age followed by a steep decline over the next few years which continues, although with a diminishing slope, throughout the adult years. Thus, the substantial decline in arrests in the later teens and early 20s found for the high chronic group in the current sample is in keeping with the Laub and Sampson (2003) findings for a much earlier cohort. The yearly patterns of arrests they presented also are not smooth across time (i.e., show more of a zig-zag decline pattern), and a similar effect may account for the upcurve in the mid 20s found in the current study. On the other hand, it seems likely that the renewed upsurge could be partly due to a methodological artifact resulting from right-censoring of the data and the chosen growth model parameterization (i.e., cubic growth function). For these reasons, it should be interpreted with great caution.

A final aspect of note of the current findings that is not predicted by the dual taxonomy career models was the substantial number of men who experienced a first arrest in adulthood. Adult onset of offending (after age 18 years) occurred for 17% of the sample. Of those adult onset men, a substantial proportion (almost one third) were in the high-level chronic group and, therefore, had five or more arrests across the adult period. Thus, it was not the case that the adult onset men all showed relatively trivial crime careers. These findings are consistent with prior studies showing that a sizable portion of adult offenders do not have records of juvenile police contacts. As reviewed by Blumstein, Cohen, Roth, and Visher, (1986), findings of a number of long-term studies of criminal careers indicated that a prevalence for adult onset of around 17% appeared modal. Overall, the findings suggest the need for modification of existing developmental taxonomies of life-span criminal behavior.

Cross tabulation of self-report trajectory groups with arrest trajectory groups revealed significant associations between the two sets of groupings. Almost 58% of the high-level chronic arrest trajectory members were also members of the self-report chronic high-level trajectory, and none of them belonged to the three low-level offending self-report trajectories (i.e., decreasing low-level, rare, and nonoffenders). Members of the rare-offender arrest trajectory group, on the other hand, were distributed across all six self-report trajectory groups, with just about 20% belonging to either rare or nonoffender self-report groups, but about 24% belonging to one of the two chronic self-report trajectory groups. This result illustrates that official record data on crime represent a conservative estimate of the amount of criminal activity and thus underestimate an individual's engagement in offending behavior across the lifespan. On the other hand, it might be argued that such discrepancies between findings for self-report versus official records offending trajectories are nothing more than a measurement artifact because, as Hindelang, Hirschi, and Weiss (1979) posited in the 1970s, self-report data on crime probably tap a more trivial domain of offending than do official data. However, the self-reports in the OYS included several nontrivial offenses, including theft, property damage, and violence, and supplemental analyses indicated that 75% of the self-report chronic high-level offenders also had a lifetime history of five or more official arrests (see Wiesner, Kim, and Capaldi, 2005). Therefore, we concur with Nagin et al. (1995) that the discrepancy between self-report versus official record trajectory findings cannot fully be explained as just a measurement artifact.

Some precautions are warranted in interpreting the findings from this study. First, the study was conducted with data from a mostly Caucasian sample of at-risk young men, and the effects of sample diversity need to be studied more closely. This especially pertains to studying trajectories of offending for female samples. Second, identification of the offending trajectory groups was based on right-censored data, which is necessarily the case when studying ongoing behaviors. This may have introduced some bias, especially among the high-level chronic group, as described above. Eggleston, Laub, and Sampson (2004) also found that the trajectories of those whose offending careers were still unfolding at the end of the observation period were most affected by varying lengths of follow-up. Future data collection with this sample will permit assessment of such effects. Third, the sample size was relatively small. However, Sampson, Laub, and Eggleston (2004) examined the effect of sample size on a number of trajectory groups identified for criminal behavior and found that the number of groups stabilized at a sample size of about 200 participants. D'Unger and colleagues (1998) also found that the optimal number of groups did not vary as a function of sample size above this range. Loughran and Nagin (2005) conducted a simulation study for the Poisson-based model in SGM and concluded that the two key asymptotic properties of maximum likelihood estimates, unbiasedness and normality, are achieved in relatively small samples (in their case, $N = 500$ was the smallest sample size under examination). Despite these caveats, this longitudinal study contributed to the existing literature on distinctive trajectories of offending and suggested important avenues for further research.

In conclusion, the pattern of findings from this study on officially recorded arrest trajectories and from prior research with the same sample on self-reported offending trajectories overall suggested limited convergence of results across different assessment methods of offending behavior. Such limited convergence was to be expected given the much larger prevalence of crime when assessed by self-report as compared with official records. The findings suggest that our understanding of crime careers may be increased by using these complementary data sources to examine crime trajectories for the same sample.

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## Biographies

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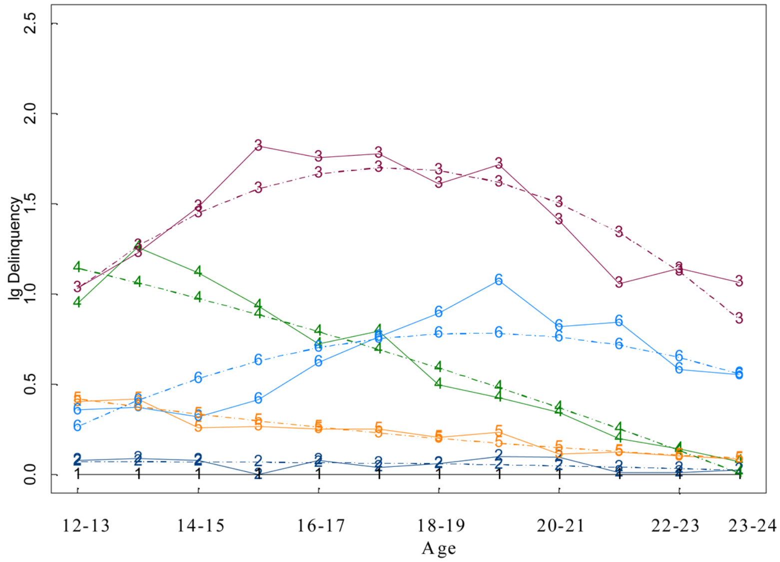


**Figure 1.**
Fitted (Dashed) versus Empirical (Solid) Growth Curves For Self-Reported Offending (from Wiesner and Capaldi, 2003)

*Note*: Class 1 contains *Nonoffenders* (4.9%, *n* = 10), Class 2 *Rare Offenders* (11.3%, *n* = 23), Class 3 *Chronic High-Level Offenders* (15.7%, *n* = 32), Class 4 *Decreasing High-Level Offenders* (27.9%, *n* = 56), Class 5 *Decreasing Low-Level Offenders* (21.6%, *n* = 44), and Class 6 *Chronic Low-Level Offenders* (18.6%, *n* = 38). Reprinted with permission from Sage Publications (2003).

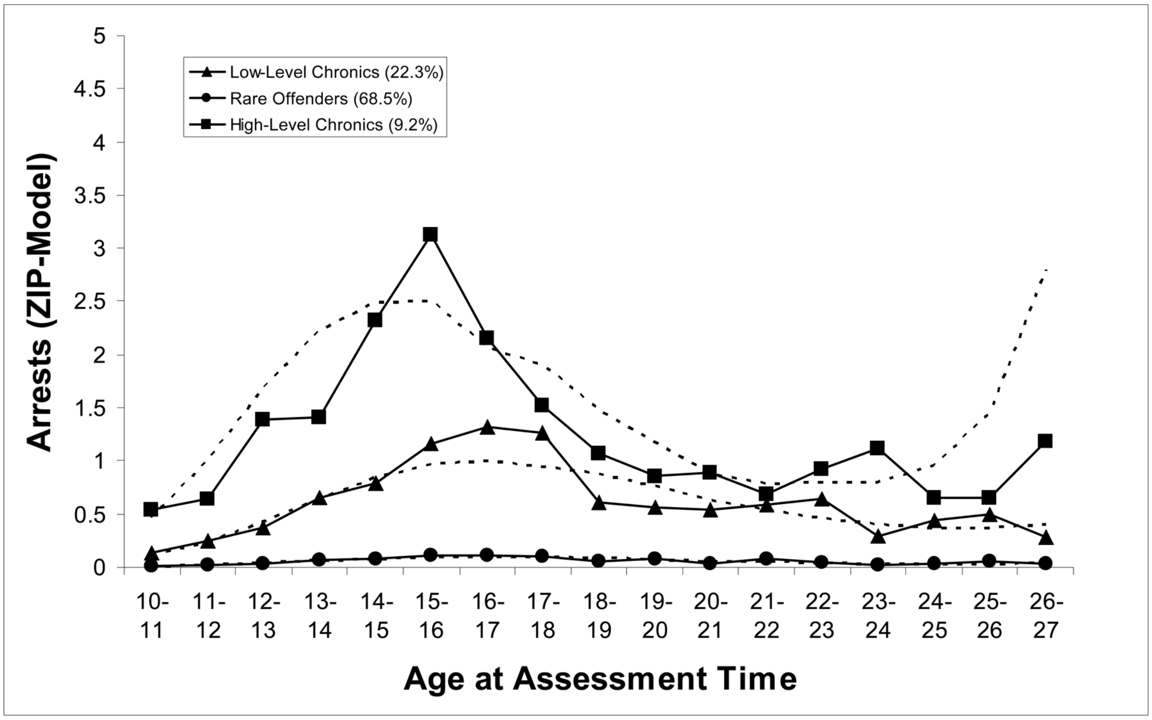


**Figure 2.**
Fitted (Dashed Lines) versus Empirical (Solid Lines) Trajectories of Officially Recorded Offending for 203 Young Men
*Note*: Empirical trajectories represent the observed arrest rates; fitted trajectories are statistically adjusted for exposure time.

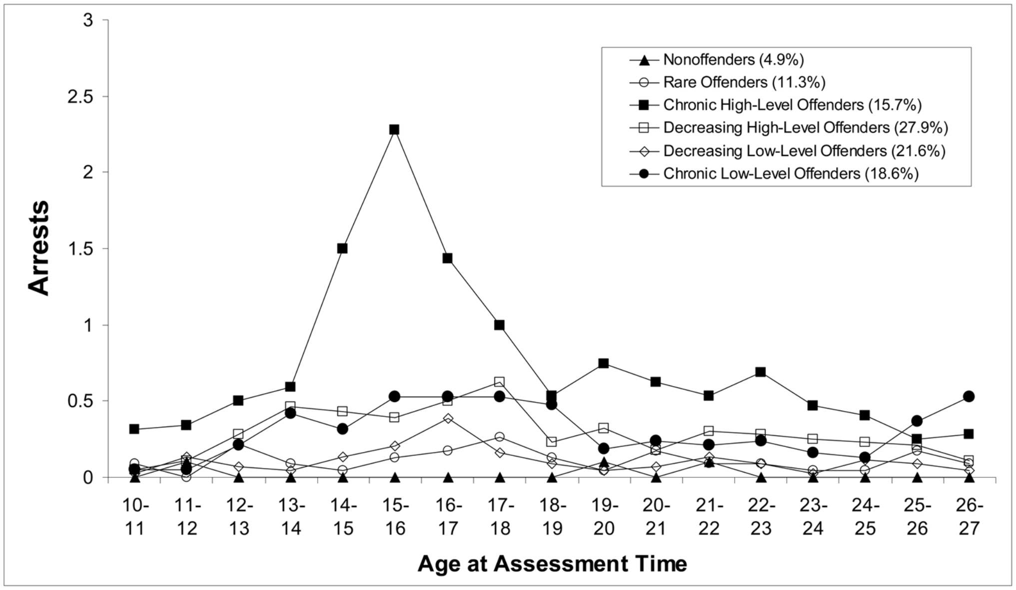


**Figure 3.**
Officially Recorded Offending for the Six Self-Report Offender Groups ($N = 203$) from Wiesner and Capaldi (2003)

**Table 1**

Arrest Activity of 203 Young Men by Self-Reported Offending Behavior

| **Number of Self-Reported Index and Nonindex Offenses (Ages 12/13 thru 23/24 Years)** | **No. of Men** | **No. of Men Arrested at Least Once** | **Fraction of Men Arrested-** | **Mean No. of Arrests** |
|---|---|---|---|---|
| 0 | 10 | 2 | 0.20 | 0.20 |
| 1–2 | 12 | 5 | 0.42 | 1.17 |
| 3–5 | 11 | 7 | 0.64 | 1.82 |
| 6–10 | 8 | 2 | 0.25 | 0.38 |
| 11–20 | 14 | 9 | 0.64 | 1.21 |
| 21–50 | 24 | 14 | 0.58 | 2.08 |
| 51–100 | 28 | 20 | 0.71 | 2.82 |
| 101–200 | 14 | 8 | 0.57 | 1.21 |
| 201+ | 82 | 66 | 0.80 | 7.79 |
| Number of Self-Reported Index Offenses(Ages 12/13 thru 23/24 Years) | No. of Men | No. of Men Arrested at Least Once | Fraction of Men Arrested | Mean No. of Arrests |
| 0 | 70 | 30 | 0.43 | 0.74 |
| 1–2 | 26 | 18 | 0.69 | 1.96 |
| 3–5 | 26 | 16 | 0.62 | 3.65 |
| 6–10 | 20 | 17 | 0.85 | 5.20 |
| 11–20 | 23 | 18 | 0.78 | 4.74 |
| 21–50 | 16 | 12 | 0.75 | 9.56 |
| 51–100 | 12 | 12 | 1.00 | 11.67 |
| 101–200 | 5 | 5 | 1.00 | 9.60 |
| 201+ | 5 | 5 | 1.00 | 17.80 |

*Note*. The fraction of men arrested is given by the number of men with one or more arrests divided by the number of men in the given self-reported offense category.

**Table 2**

Model Fit Results for ZIP Trajectory Models (*N* = 203)

| | Model Fit | | | | | Final Three-Class Model | | | |
|---|---|---|---|---|---|---|---|---|---|
| **# Classes** | **BIC** | **AIC** | **PP** | **BIC log Bayes Factor Approximation** | **Class** | **Proportion** | **Average Class PProb** | **Median Class PProb** | **OCC** |
| 1 | −2348.79 | −2340.51 | .000 | ----- | Rare Offenders | .685 | .979 | .998 | 21.44 |
| 2 | −2076.26 | −2059.70 | .000 | 545.06 | Low Level Chronics | .223 | .952 | .993 | 69.11 |
| 3 | −2033.62 | −2008.77 | 1.000 | 85.28 | High Level Chronics | .092 | .926 | .988 | 123.50 |
| 4+ | No convergence to stable solution | | | | | | | | |

*Note*. *BIC* = Bayesian Information Criterion, *AIC* = Akaike Information Criterion, *PP* = Posterior Probability of Being the Correct Model, BIC log Bayes Factor Approximation = $2\log_e(B_{10})$, *Class PProb* = Posterior Probabilities of Class Membership, *OCC* = Odds Correct Classification.

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**Table 3**

Arrest Trajectory Group Characteristics (*N* = 203)

| | Arrest Trajectory Groups from Court Records | | | |
|---|---|---|---|---|
| | **Rare Offenders(68.5%)** | **Low-Level Chronics(22.3%)** | **High-Level Chronics(9.2%)** | **Test-Statistic** |
| *Total Official Arrests until Ages 26–27 Years (%)*: | | | | |
| Men with 10+ arrests | 0.0 | 53.5 | 94.7 | $\chi^2_{(2)}$ =130.75*** |
| Men with 5+ arrests | 0.7 | 97.7 | 100.0 | $\chi^2_{(2)}$ =193.72*** |
| Men with 4+ arrests | 4.3 | 100.0 | 100.0 | $\chi^2_{(2)}$ =177.21*** |
| Men with 3+ arrests | 13.5 | 100.0 | 100.0 | $\chi^2_{(2)}$ =134.45*** |
| Men with 2+ arrests | 27.7 | 100.0 | 100.0 | $\chi^2_{(2)}$ = 90.15*** |
| Men with 1+ arrests | 58.2 | 100.0 | 100.0 | $\chi^2_{(2)}$ = 36.57*** |
| *Total Violent Arrests until Ages 26–27 Years (%:)* | | | | |
| Men with 2+ *violent* arrests | 0.7 | 32.6 | 42.1 | $\chi^2_{(2)}$ = 53.03*** |
| Men with 1+ *violent* arrests | 10.6 | 65.1 | 73.7 | $\chi^2_{(2)}$ = 70.02*** |
| *Self-Report Offender Trajectory Group (%)*: | | | | |
| Nonoffenders (4.9%) | 7.1 | 0.0 | 0.0 | |
| Rare Offenders (11.3%) | 13.5 | 9.3 | 0.0 | |
| Decreasing Low Level (21.6%) | 29.1 | 7.0 | 0.0 | |
| Decreasing High Level (27.9%) | 26.2 | 37.2 | 15.8 | |
| Chronic Low Level (18.6 %) | 18.4 | 16.3 | 26.3 | |
| Chronic High Level (15.7%) | 5.7 | 30.2 | 57.9 | |
| Σ Total | 100.0 | 100.0 | 100.0 | $\chi^2_{(10)}$ = 58.68*** |
| *Early Starter/Late Starter Classification (%)*: | | | | |
| Early Starters (25.6%) | 8.5 | 62.8 | 68.4 | |
| Late Starters (28.6%) | 28.4 | 32.6 | 21.1 | |
| Adult Starters (17.2%) | 22.0 | 4.7 | 10.5 | |
| Nonoffenders (28.6%) | 41.1 | 0.0 | 0.0 | |
| Σ Total | 100.0 | 100.0 | 100.0 | $\chi^2_{(6)}$ = 85.31*** |