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Methodological Sensitivities to Latent Class Analysis of Long-Term Criminal Trajectories

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A recent and growing body of research has employed a semiparametric group-based approach to discover underlying developmental trajectories of crime. Enthusiasm for such latent class models has not been matched with robustness and sensitivity analyses to determine how conclusions from the method vary according to fundamental methodological problems that inhere in criminological data. Using a sample of 500 delinquent boys and their official crime counts from ages 7 to 70, this paper systematically addresses how three concerns in longitudinal research—(a) length of follow-up, (b) the inclusion of exposure time (incarceration), and (3) data on involuntary desistance through death—influence our inferences about developmental trajectories. While there is some evidence of stability, a comparison of group number, shape, and group assignment across varying conditions indicates that all three data considerations can alter trajectory attributes in important ways. More precisely, longer-term data on offending and the inclusion of incarceration and mortality information appear to be key pieces of information, especially when analyzing high-rate offending patterns.

KEY WORDS: semiparametric group-based method; sensitivity analysis; longitudinal research methods; trajectories.

1. INTRODUCTION

Debates about continuity and change in offending over the life course have animated criminology over the last decade. There are several methods currently employed to estimate developmental trajectories and within-individual change in a longitudinal perspective, including hierarchical linear modeling, growth curve analysis, and semiparametric mixture models, to name a few (for a discussion on modeling longitudinal trajectories see, e.g., Bushway *et al.*, 1999; Raudenbush, 2001). This paper focuses on the

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semiparametric mixture model, but we believe our conclusions hold merit for developmental research in general.

Semiparametric group-based approaches, also known as latent class analysis, offer a number of advantages to criminological research. First, this method is specifically designed to analyze longitudinal data and is well-suited to research questions that seek to contrast discrete groups of offenders who are homogeneous within their trajectory yet distinct from those following other trajectories (e.g., those who persist in offending through adulthood vs. those who desist from offending in late-adolescence). A second advantage is that the semiparametric group-based approach is more systematic in the way it categorizes offenders. Prior research has categorized offenders using subjective assignment procedures established a priori while the semiparametric group-based approach identifies distinctive groups by applying a formal, objective statistical criterion, the Bayesian Information Criterion, to determine the appropriate number of groups in a population rather than assuming them. Third, in addition to the shape of the trajectory, this approach also provides posterior probabilities that indicate the precision of group assignment and are used to assign individuals to the different groups. Finally, the semiparametric group-based approach accommodates missing data in the estimation and therefore, those who have missing information in the outcome variable for several time periods will not be excluded from the analysis.

These many advantages along with the increasing interest in modeling stability and change in problem behaviors has led to a rapid growth in the body of research using the semiparametric group-based approach. Due to this method's growing popularity, we believe that researchers need to assess the robustness of the trajectory attributes under varying conditions. In particular, three methodological considerations are used in this paper to examine how trajectories of offending are affected by these varying conditions. These three considerations are the length of follow-up in the sample (i.e., the number of data points used in the model), the inclusion of incarceration information to account for exposure time on the street, and the inclusion of mortality information to safeguard against treating those who are dead as desisters from crime. To be clear, these data considerations are not unique to the semiparametric group-based approach as these are important to consider when employing any longitudinal method that investigates trajectories of offending over the life course.[4] However, this method has not been subjected

[4] In addition, these issues are not unique to offending in that they can affect the identification and estimation of trajectories for a number of other outcomes. For instance, length of follow-up could affect trajectory attributes of aggression, reading ability, or employment, to name a few.

to a sensitivity analysis to date. Thus, the purpose of this paper is to test the robustness of the semiparametric mixture model specifically with respect to these data considerations.

2. SEMIPARAMETRIC GROUP-BASED APPROACH

Before we address these methodological considerations, we turn to a brief description of the semiparametric group-based approach as outlined in Nagin (1999) (see also Jones *et al.*, 2001; Nagin and Land, 1993; Nagin and Tremblay, 2001, for more details on this approach). This method identifies a number of developmental trajectories within a population using a polynomial link function between age and the outcome. There are three types of distributions used with the semiparametric group-based approach and the selection of the appropriate distribution and its accompanying linking function depends on the form of the outcome variable of interest. For instance, the Poisson model is most appropriate when the outcome variable is count data, the censored normal should be used with scales or other data that is truncated or has clustering at the minimum and maximum values, while the logit model is most appropriate for dichotomous variables. The present research uses a semiparametric mixed Poisson regression model to analyze criminal offending over the life span in order to investigate the robustness of the results given differing lengths of follow-up and consideration of time on the street (exposure) and mortality. These models are estimated using the SAS-based TRAJ procedure described by Jones *et al.* (2001).

In general, the mixed Poisson model assumes that the population is comprised of discrete Poisson distributions with a λ rate of offending. Each developmental trajectory assumes a polynomial relationship that links age and offending as illustrated by the equation

$$\log \lambda_{it}^{j} = \beta_0^j + \beta_1^j \text{age}_{it} + \beta_2^j \text{age}_{it}^2 + \beta_3^j \text{age}_{it}^3 \tag{1}$$

where λ_{it}^{j} is the predicted number of offenses for person i in group j at time period t, age_{it} is the age of person i at time period t, age_{it}^2 is the squared age of person i at time period t, and age_{it}^3 is the cubed age of person i at time period t. The coefficients β_0^j, β_1^j, β_2^j and β_3^j structure the shape of the trajectory for each group j. Although every individual in each group is constrained to the same slope and intercept of that trajectory, these parameters which determine the level and shape of the trajectory are free to vary by group.[5]

[5] The present analysis uses either a quadratic function or a cubic function depending on the model. For the full time span (age 7 to 70), a cubic relationship is more appropriate to allow for more flexibility in the shape of the trajectory. However, when models with shorter time periods are estimated (age 7 to 25, 7 to 32, or 7 to 45), a quadratic function is used.

The trajectory method estimates these model parameters for a fixed number of groups using maximum likelihood. The optimal number of groups is determined by the Bayesian Information Criterion (BIC) which can inform the selection of the best model for comparison of both nested and unnested models (see D'Unger *et al.*, 1998; Nagin, 1999). The BIC is estimated using the following equation

$$\mathrm{BIC} = -2\log(L) + \log(n) * k \tag{2}$$

where L is the maximum likelihood, n is the sample size, and k is the number of model parameters. Although the Bayesian Information Criterion has been emphasized as the primary criterion to assess the optimal number of groups, the model selection process is often more complex and thus, group selection remains somewhat subjective. As Nagin and Land note in their original article on this subject, the groupings "may be seen as only an approximation of a postulated underlying continuous dimension of hidden heterogeneity in offending propensity" (1993, p. 357). Since these groupings are abstractions or approximations and not a true reflection of reality, researchers tend to use the BIC as one criterion for choosing the number of groups, but not the sole criterion. For instance, Brame *et al.* (2001a) find a six group model to be the optimal model based on the BIC for their childhood aggression analysis and yet they "describe the four-group model because the results from this more parsimonious solution are qualitatively similar" (2001, p. 506). In the majority of the estimated models in this analysis, the BIC is used to select the optimal model.

Lastly, this procedure assigns each individual a probability of membership in each group. This posterior probability is determined using the equation

$$\hat{P}(j \mid Y_i) = \frac{\hat{P}(Y_i \mid j)\hat{\pi}_j}{\sum_j \hat{P}(Y_i \mid j)\hat{\pi}_j} \tag{3}$$

where $\hat{P}(Y_i \mid j)$ refers to the probability of observing the offending pattern (Y_i) conditional on membership in group j for person i, and $\hat{\pi}_j$ is the estimated proportion of the population in group j. Based on these probabilities, each individual is assigned to the group displaying the largest group assignment probability. In other words, individuals are assigned to the group to which they are most likely to belong based on their offending patterns. According to Nagin, these posterior probabilities "are among the most useful products of the group-based modeling approach" (1999, p. 149). The final result from the semiparametric mixed Poisson method then is a number of groups of individuals who demonstrate similar patterns of offending over time.

3. RESEARCH USING THE GROUP-BASED APPROACH

Since Nagin and Land first introduced this method in 1993, there has been a small, but growing body of research which uses the semiparametric group-based approach to study developmental trajectories of a variety of behavioral outcomes. For example, several researchers have analyzed the Cambridge Study of Delinquent Development sample with the majority of these studies estimating trajectories of official convictions for the age range of 10 to 32 years of age (see e.g., D'Unger *et al.*, 1998; Jones *et al.*, 2001; Nagin, 1999; Nagin and Land, 1993; Roeder *et al.*, 1999). Researchers have also used the group-based approach to investigate police contacts in the 1945 and 1958 Philadelphia Birth Cohorts. These studies have primarily focused on the males, ages 8 to 18 or 8 to 26 (see e.g., Brame *et al.*, 2001b; D'Unger *et al.*, 1998; Land *et al.*, 1996).

In addition, several analyses have investigated the non-criminal outcomes of physical aggression, hyperactivity, and opposition scales using teacher ratings of 1037 white males from Montreal. These behavioral outcomes are assessed at age 6 and again annually from age 10 to 15 (see e.g., Brame *et al.*, 2001a; Jones *et al.*, 2001; Nagin, 1999; Nagin and Tremblay, 1999). Still others have estimated developmental trajectories of aggressive and non-aggressive conduct problems for boys and girls at ages 9, 11, 13, and 16 (Maughan *et al.*, 2000) and self-reported counts of binge drinking for males and females, ages 13 through 16 and at age 18 (Hill *et al.*, 2000) using a variety of data sets.

While a number of researchers in several disciplines are using the semiparametric group-based approach to investigate stability and change in a variety of outcomes, there are still unanswered questions about how this model behaves under various conditions. How does length of follow-up affect estimation with respect to the resulting trajectory number, shape, and membership? In other words, how sensitive are the results when 60 years of data are used vs. 6 or 16? In a similar vein, how does the inclusion of incarceration information affect the attributes of the offending trajectories identified by the semiparametric group-based approach? Are these attributes stable across a model that assumes all offenders are eligible to offend in the community 365 days of each year vs. one that takes into account the actual number of days a person was "free" to offend in the community (i.e., not incarcerated)? Finally, we investigate how the exclusion of death information from an offender's criminal history can affect the estimation of trajectories using the semiparametric group-based approach. Specifically, do trajectory group shapes and membership change substantially between a model that accounts for mortality among its sample members and one that omits this pertinent information? This paper addresses these issues as well as identifies other potential data considerations for future research.

3.1. Length of Follow-up

The consensus from the current body of literature which employs the semiparametric group-based approach suggests that between three and five trajectory groups best fit the data with some combination of a relatively small high-rate chronic group, an adolescent-peaked desister group, and a low-rate or non-deviant group. However, what is apparent from these analyses is that they all have relatively short follow-up periods. In fact, a thorough review of the extant literature shows that, to date, 25 years of data is the longest length of follow-up (Laub *et al.*, 1998) with the majority of the analyses using approximately 15 years of information or less.

Based on this realization, questions arise regarding the potential effect of length of follow-up on the trajectory patterns produced from the semiparametric group-based approach. Do the shape of the groups and/or the peak ages of a developmental trajectory change when more years of data are available? Is an individual assigned to the same trajectory pattern (i.e., low-rate chronic, high-rate chronic, desister, etc.) regardless of the number of years analyzed or do individual patterns of offending change over time to the extent that trajectory group membership also changes? In other words, what percentage of people continue to appear in the same trajectory group when different lengths of follow-up are employed? Researchers who use the semiparametric group-based approach need to be cognizant of how length of follow-up may affect their results with respect to group number, peak ages, group shape, and group assignment.

3.2. Incarceration

As Piquero *et al.* (2001) note, a number of longitudinal studies of offending have neglected to take incarceration time into account. This fact is especially true for investigations that have employed the semiparametric group-based approach, as Piquero *et al.* (2001) is the only one we are aware of to date. In their analysis, they predict that the high-rate offenders would be most affected by an added parameter of exposure time on the street since these are the offenders who are most likely to have been incarcerated. More explicitly, if a person commits two offenses per year and is not incarcerated in that year, their rate of offending would be two offenses per year free. However, if that person were only on the street for half of the year and incarcerated for the other half of the year, his or her rate of offending should be four offenses per year free. If incarceration time is not taken into account, the predicted rate of offending could be underestimated.

Using data on 272 male parolees from the California Youth Authority, Piquero *et al*. (2001) found that indeed, incarceration time affected the trajectory shapes. In the analysis without incarceration time, 92% of the sample appear to be on a desisting trajectory by their late 20s. However, once exposure time is added to the model, only 72% of the population shows a pattern of desistance. It becomes clear that neglecting incarceration time can both underestimate the level of crime as well as distort the shape of the trajectory. Thus, there is good reason to believe that the inclusion or exclusion of time on the street in the measurement of the rate of criminal behavior will affect trajectory analyses of offending. How does this inclusion affect the trajectory shape, peak ages, and/or group number? Also, at the individual level, is there consistency in trajectory group assignment across the two models with and without exposure time?

3.3. Mortality

The third issue addresses how the inclusion or exclusion of mortality information can affect trajectory group shape and membership. When studying age and crime into the adult years, specifically when using official data, a common method of obtaining offending information is to search criminal records of sample members. Those who have no offense record for that time period are assumed to have not offended and thus are coded with zero offenses. One concern with this technique is that those who do not appear in criminal record checks may *not* have zero offenses during that time period but may have in fact died. Therefore, dead individuals will show patterns of desistance since they would not show up in official records and subsequently be coded as having zero crimes. This circumstance poses a problem for any type of method that aims to distinguish longitudinal offending patterns. In addition, we know from empirical research that high-rate offenders have an increased chance of death (Lattimore *et al*., 1997; Laub and Vaillant, 2000; Reiss, 1989) and thus, the high-rate chronic offender population should be most affected by the exclusion of mortality data. Again we ask, do group characteristics change depending on whether mortality is taken into account? Also, are the changes most apparent in the high-rate chronic group?

4. SAMPLE AND MEASURES

This analysis uses data from the Gluecks' *Unraveling Juvenile Delinquency* (1950) archive and the follow-up data collected by John Laub and

Robert Sampson (for more information, see Sampson and Laub, 1993; Laub and Sampson, 2003). The total sample includes 1000 males from Boston who were born between 1925 and 1932. While the total sample is comprised of 500 juvenile delinquent males selected from two reform schools in Massachusetts and 500 matched non-delinquent males selected from the Boston public school system, this study focuses on the delinquent sample. The analysis uses information on annual offense counts for ages 7 to 70 to model trajectories of offending.[6]

The offense counts for ages 7 up to 32 were compiled by the Gluecks' research team using a variety of local, state, and national record data. In their follow-up study, Laub and Sampson compiled offense counts from ages 32 up to 70 from Massachusetts criminal history records and FBI "rap sheets" for each individual (see Laub and Sampson, 2003, for more details). Offense counts are coded by crime type, including violent, property, drug and alcohol offenses, and an "other" category. The total offense count measure used in this analysis is simply a sum of the crime-specific annual offense counts. Examples of violent crimes include homicide, robbery, and assault; examples of property crimes include burglary and vandalism; examples of drug and alcohol crimes include drunkenness and narcotics selling and possession; and examples of the "other" category include a variety of behaviors such as disorderly conduct, resisting arrest, and violations of probation or parole.

Incarceration data for ages 7 up to 32 were available from the criminal history data collected by the Gluecks' research team and coded by Laub and Sampson (see Sampson and Laub, 1993, for details). Data are available on the actual number of days per year that a person was incarcerated, and thus not eligible to incur any official offense on the street. Finally, the mortality data were obtained by Laub and Sampson from both state (e.g., Massachusetts Bureau of Vital Statistics) and national (e.g., National Death Index) death records that were then integrated with the official criminal histories (see Laub and Sampson, 2003).

5. ANALYTIC STRATEGY

Overall, this analysis investigates how the varying conditions of data outlined above can affect trajectory patterns produced by the

[6] While the original sample includes 500 men, the sample used in this analysis is restricted to 480 of the original 500 delinquents with available data. This analysis uses the delinquent sample and focuses on serious persistent offenders and their offending patterns. Thus, by design, there is no non-offender group. Since the semiparametric group-based approach models within-individual change, the exclusion of a non-offender group should not affect the results among the offender trajectory groups.

semiparametric mixed Poisson model. The first part of the analysis investigates the effects of differing lengths of follow-up. The Glueck data are particularly well-suited to investigate this issue of length of follow-up since this data set contains information on offense counts from ages 7 to 70. This analysis varies the length of follow-up time and estimates four separate models for the age ranges 7 to 25, 7 to 32, 7 to 45, and 7 to 70 for the outcome variable of total offense counts per year per person.[7]

The second section addresses the effects of including incarceration information. In this section, two separate semiparametric mixed Poisson models of total crime counts are estimated for the age range of 7 to 32. The first model does not take incarceration time into account while the second model includes an incarceration parameter in the estimation. This added parameter incorporates the amount of time each person spent in the community each year. With this additional parameter, λ_{it}^{j} from Eq. (1) becomes a weighted λ representing the predicted number of offenses that person i in group j would have committed if he had been free for the entire time period t (i.e., 365 days of the year).

The final part of the analysis investigates the effects of excluding mortality information on trajectory groupings and patterns. Two models of total crime are estimated, one model that does not include death information for the age range of 7 to 45 and one model that does include the integration of death information during this same age period.[8] More specifically, in one model, individuals who have died have zero offenses coded after the age of death while these same individuals have "not applicable" codes for number of offenses after the age of death in the second model. One advantage mentioned earlier of the semiparametric group-based procedure is that this procedure accommodates missing data in the outcome variable such that no one is excluded from the analysis even if they have missing information for several time periods (Jones *et al.*, 2001). Given that there are 63 time periods and that approximately half of the sample is dead by age 70, the accommodation of missing data such that all available information is used becomes an important advantage.

[7] Mortality is accounted for in each trajectory model for the length of follow-up analysis, but incarceration time is not controlled. The fact that incarceration information was only collected to age 32 precludes our ability to compare the shorter age ranges with the longer age ranges of 7 to 45 and the full life course (i.e., 7 to 70) while controlling for incarceration time. The age ranges were selected to capture the transition from adolescence to adulthood and to coincide with the interview waves of the Gluecks' follow-up study (see Sampson and Laub, 1993).

[8] Age 45 was selected because we know high-rate offenders in the Glueck study are more likely to die earlier compared with non-offenders (see Laub and Vaillant, 2000).

6. RESULTS

6.1. Length of Follow-up

How does length of follow-up affect trajectory number, shape, and group membership? Figure 1 shows the trajectory models of total offending for the four age ranges. Overall, length of follow-up does not drastically affect the number of distinct developmental trajectories identified by the semiparametric mixed Poisson model. The optimal model for the 7 to 25 age range is four groups (Fig. 1a). The analysis for the 7 to 32 and 7 to 45 age ranges find five groups to be optimal (Figs. 1b and 1c) and the 7 to 70 years model shows six groups to be the optimal number of groups (Fig. 1d).[9] It is interesting to note that when limited to the shortest age range (7 to 25), the semiparametric mixed Poisson method does not identify a high-rate chronic group.

For each model we have named the trajectory groups based on the relative offending patterns of the sample in that model.[10] The percentage in parentheses next to each group's label represents the estimated proportion of the population belonging to each group. The first group is the "low-rate chronic" group who display low levels of offending throughout the sampling period. The "moderate-rate chronic" group displays a higher level of offending than the low-rate chronic group throughout the entire sampling period. There is also a "high-rate chronic" group who displays the highest level of offending throughout the time span. The "classic desister" trajectory follows the familiar age-crime curve. These offenders peak in adolescence and desist by their early- to mid-20s. Finally, the "moderate-rate desister" group displays a desistant pathway but at a higher level of offending, with a later peak age, and a later age of desistance than the "classic desisters."

Overall, trajectory shape, peak age, and group membership seem to be affected by length of follow-up, although there are some groups that are more affected than others. To begin, trajectory shape and peak age are compared. To best display these results, Figs. 2 through 5 show the same group for the different age ranges on one graph in order to compare group shapes and peak ages based on length of follow-up.[11]

[9] The mean group assignment probabilities for the length of follow-up analysis range from 84% to 99%.

[10] The group names are consistent across all of the models for ease of comparison. This consistency in terminology is used for heuristic purposes and is not meant to be a reification of these groups. Also, although the 7 to 70 model shows all groups as eventually desisting, we continue to use the term "chronic" in the group names to indicate chronic offending for the majority of the sampling period and again, for ease of comparison.

[11] Note that not all groups are explicitly compared. The groups selected for comparison are those that best illustrate the issues at hand.

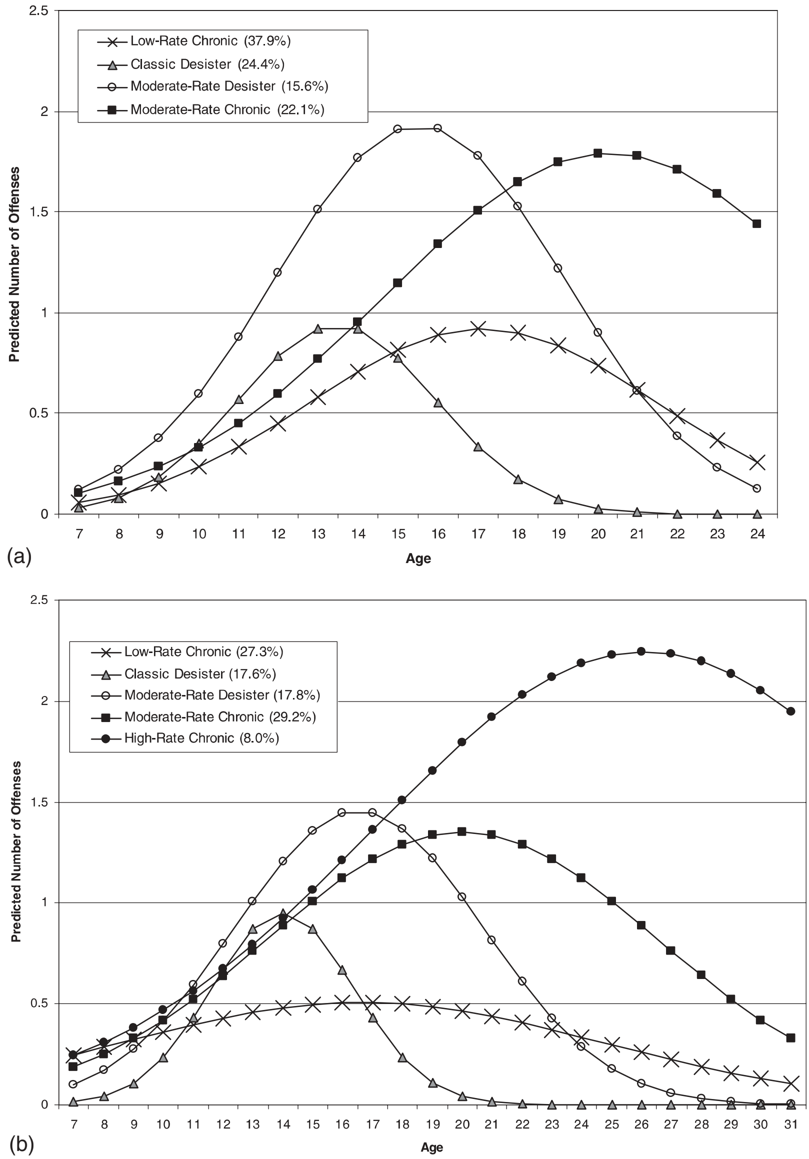

Fig. 1. Developmental trajectories of offending by length of follow-up.

The first group compared here is the moderate-rate desister group (Fig. 2). In this graph, each line represents the predicted number of offenses at each age for the moderate-rate desisters from the four separate models.

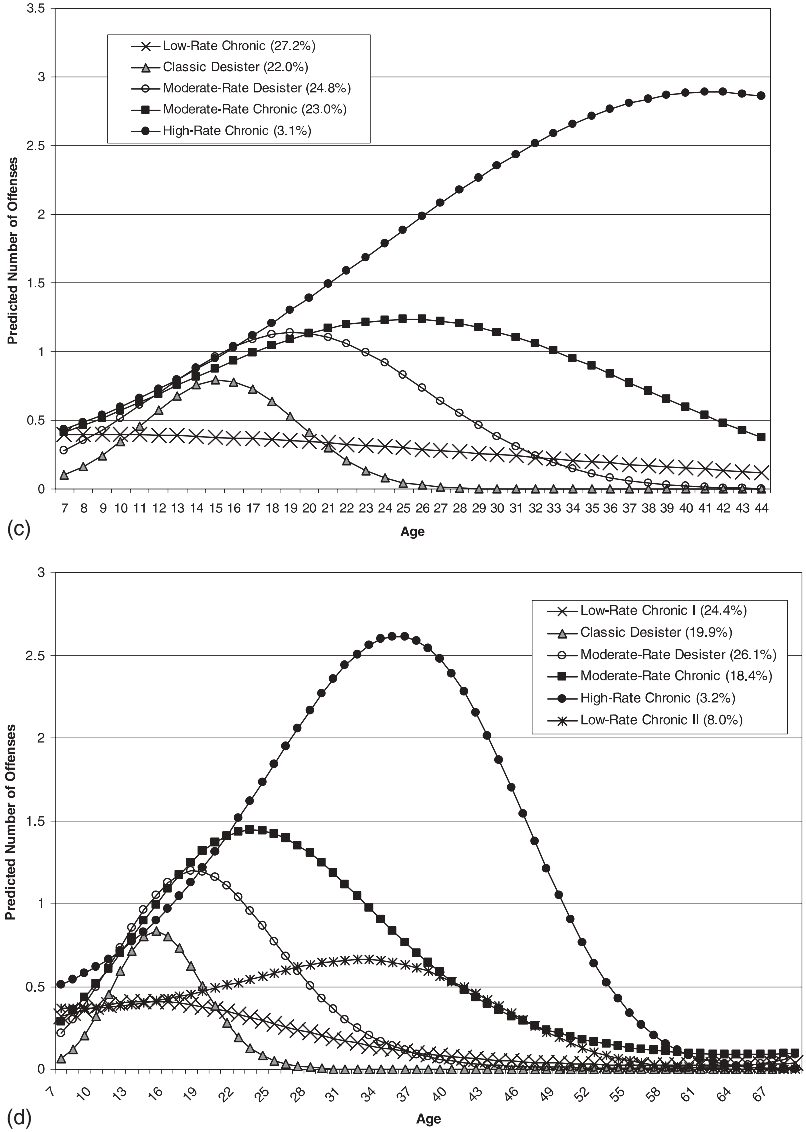

Fig. 1. Continued.

As the figure shows, when less information is used to estimate the trajectories, the group shapes change in that there is a steeper incline and decline for the shorter lengths of data. Also, the peak ages are slightly younger for these shorter age ranges. Specifically, offending peaks at age 16 to 17 for the

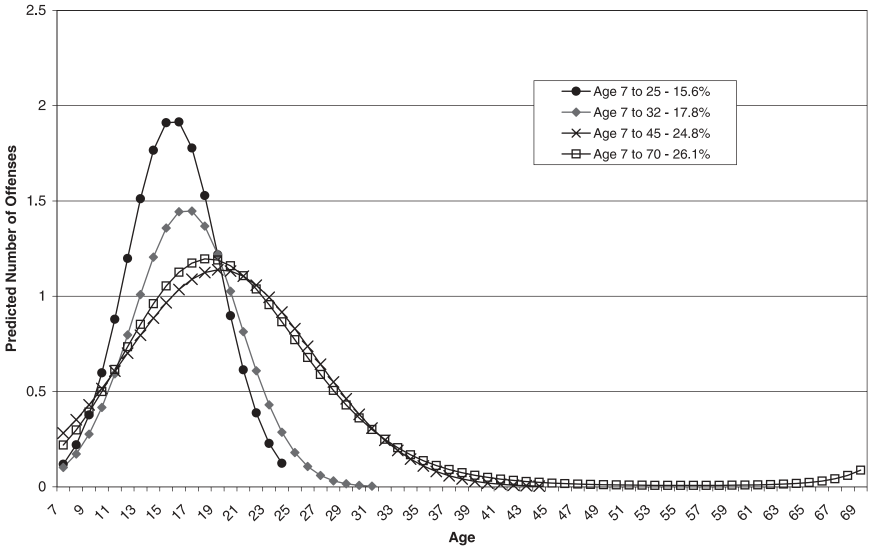

Fig. 2. Moderate-rate desister offenders, total crime: a comparison of models with different lengths of follow-up.

shorter lengths of follow-up while for the longer age ranges offending peaks at ages 18 or 19.

Figure 3 shows similar results for the moderate-rate chronic group. Again there are different shapes, especially comparing the shorter age ranges and the longer age ranges with the longer age ranges showing a more gradual decline in offending over time. In this comparison, offending is also predicted to peak at a younger age for the shorter length of follow-up trajectories. For the shorter age ranges, the trajectories peak at age 20 while for the longer age ranges the group trajectories peak closer to age 25. Figure 4 compares the different age models for the high-rate chronic groups.[12] In this comparison, the difference in peak ages is more pronounced as there is a 10 year difference. While there is a peak age of offending at 26 with 2.2 offenses per year for the 7 to 32 trajectory, there is a peak at 36 with 2.6 offenses per year when the full life span of 7 to 70 is used. Overall, based on these three graphs, it appears that for the moderate-rate desister group, the moderate-rate chronic group, and the high-rate chronic group, length of follow-up essentially changes the shape and peak ages of the predicted trajectory. This is especially true for the high-rate chronic offenders who no longer display a

[12] In this figure, there is no 7 to 25 group since there was no high-rate chronic group identified in that model.

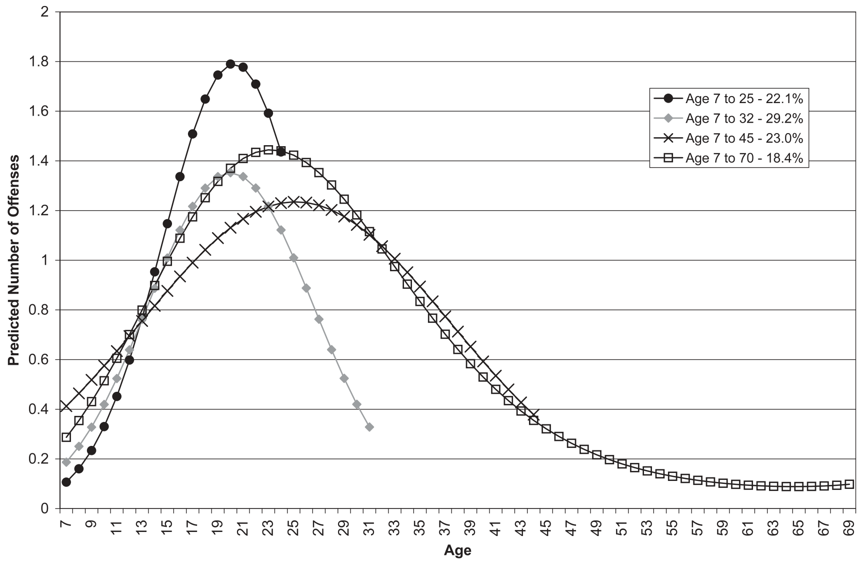

Fig. 3. Moderate-rate chronic offenders, total crime: a comparison of models with different lengths of follow-up.

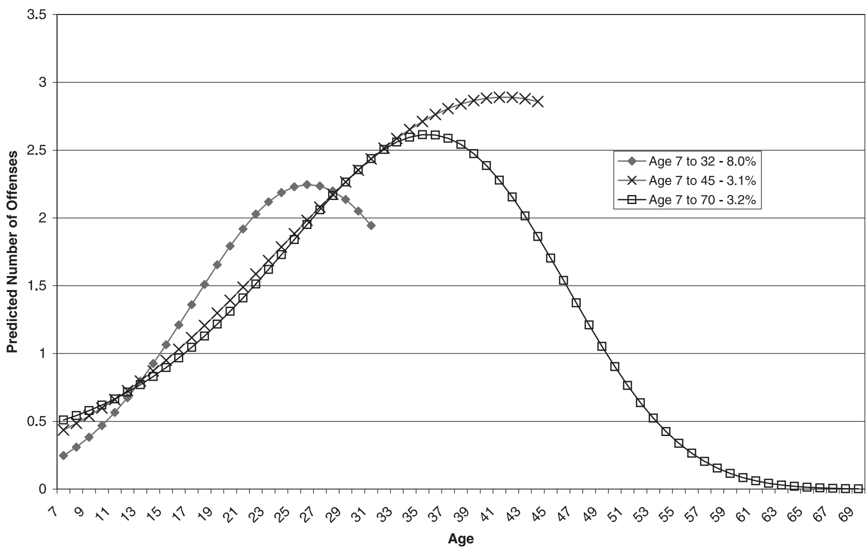

Fig. 4. High-rate chronic offenders, total crime: a comparison of models with different lengths of follow-up.

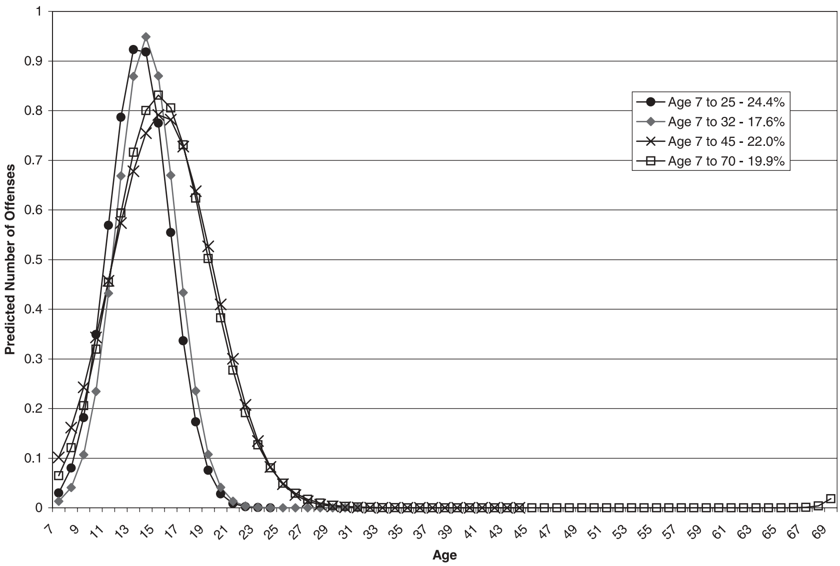

Fig. 5. Classic desister offenders, total crime: a comparison of models with different lengths of follow-up.

chronic offending pattern over the entire sampling period in the 7 to 70 model but instead show a decline in offending from age 40 to age 70. Thus, the estimated trajectories show sensitivity and instability with the varying lengths of follow-up.

However, not every group is affected so dramatically. The best illustration of this fact is the classic desister group. These offenders have finished offending by their 20s and thus, not surprisingly, there is more consistency across lengths of follow-up. Figure 5 shows the classic desister group models where the peak age is 15 to 16 for all of the trajectories regardless of length of follow-up. The shape of the trajectories also remain consistent regardless of whether more or less information is used. Thus, it appears that those groups that are most affected by the varying lengths of follow-up are those whose offending careers are still unfolding into middle and late adulthood.

The next question asks, how stable are these groups with respect to group membership? One way to assess the stability of group membership is to estimate what percentage of people "change groups." As an overall indication of stability, 49% of the men change groups when the 7 to 32 model and the 7 to 70 model are compared while only 12% of the men change groups when the 7 to 45 model and the 7 to 70 model are compared. Thus again, the longer the follow-up, the more similar the trajectory attributes correspond to those of the full life course (7 to 70). Given that this is a *latent* class analysis, the group assignments are probabilistic not exact. Therefore, in order to further investigate the instability of group assignment between models we subjected this part of the analysis to a more rigorous standard by selecting only those who had a group assignment probability of at least 0.90 in both of the models compared. The results show that among the selected group, 44% of the men change groups when the 7 to 32 and 7 to 70 model are compared while only 8% of the men change groups when the 7 to 45 and the 7 to 70 model are compared. Thus, the latent aspect of the analysis does not appear to be distorting the general conclusion of instability since there is still more instability in group membership when shorter lengths of follow-up are compared to the full life course among those with a high certainty of group assignment.

To examine the stability for each group specifically, the question becomes, what percentage of people who are identified as a moderate-rate desister in the 7 to 32 model are also identified as a moderate-rate desister in the 7 to 70 model? This estimate can also be interpreted as the probability of being assigned to the moderate-rate desister group in the 7 to 70 model given membership in that group in the 7 to 32 model. Similar to the overall findings, about half of the moderate-rate desisters (47%) from the 7 to 32 model are also in the 7 to 70 moderate-rate desister group. This percentage rises to 91% when the 7 to 45 model and the 7 to 70 model are compared. Again, more stability appears as the length of follow-up gets longer and these desisters complete their criminal careers.

The chronic groups, on the other hand, show more instability than the sample as a whole since many of these men continue to offend into late adulthood. For instance, for the high-rate chronics, only 25% in the 7 to 32 model are also identified as high-rate chronics in the 7 to 70 model while 87% of the high-rate chronics in the 7 to 45 model are also assigned to this group when ages 7 to 70 are used to estimate the trajectories. Similarly, with respect to the moderate-rate chronic group, 38% remain in the group from the 7 to 32 model to the 7 to 70 model while 75% remain in the moderate-rate chronic group from the 7 to 45 model to the 7 to 70 model.

In contrast, the classic desister group shows more stability in group membership in comparison to the chronic groups. Over half of the classic desisters in the 7 to 32 model are identified as classic desisters in the 7 to 70 model (57%) and the vast majority of the classic desisters in the 7 to 45 model also appear in this group when ages 7 to 70 are used to estimate the trajectories (89%).[13]

[13] Again, the more rigorous analysis conducted on those with a group assignment probability of at least 0.90 in both models shows a very similar pattern when the specific groups are compared.

In short, the results from the analysis thus far indicate that length of follow-up can influence group shape, peak ages, and group membership. However, this is not universally true as groups are differentially affected by length of follow-up. The high-rate or moderate-rate chronic groups who continue to offend into adulthood show the most instability while those in the classic desister group have completed their criminal careers by early adulthood and so, not surprisingly, this group shows the most stability across the models.[14]

6.2. Incarceration

As Fig. 6 shows, the semiparametric mixed Poisson method identified and estimated five distinct offending trajectories for both the model that includes incarceration time (Fig. 6b) and the model that does not include incarceration time (ages 7 to 32; Fig. 6a).[15] In accordance with predictions based on the extant literature, the trajectories that disregard time on the street show a lower level of overall offending for each group than when incarceration is taken into account.

Again, to best display the comparisons between these two models, Figs. 7 through 9 show the group shapes based on the inclusion or exclusion of incarceration time for the same groups.[16] Figure 7 shows that for the moderate-rate chronics, there are somewhat different shapes but a similar rate of incline and decline. What is most apparent is the higher predicted level of offending when incarceration is taken into account. Also, with incarceration included in the model, offending is predicted to peak at an older age (age 23 vs. age 20). With respect to group membership in these two models, we see a fair amount of instability with the moderate-rate chronic offenders. Thirty-nine percent of the moderate-rate chronics in the model

[14] Preliminary analyses comparing crime specific patterns between a 7 to 32 model and a 7 to 70 model for property, violent, and alcohol/drug offending show that the effects of length of follow-up may vary by crime type. For instance, although patterns for property crime show no clear trends, the analysis for alcohol and drug crimes reveals similar differences in group shape and peak ages seen in the analysis for total crime. Interestingly, for violent crime, the actual groups identified becomes the most important issue. For this crime type, the 7 to 32 model identified three trajectory groups—a moderate-rate chronic group, a classic desister group, and a low-rate desister group. The 7 to 70 model also identified these groups in the optimal model along with two additional groups—a high-rate desister group and a late-onset group. These two groups have been key groups of interest in past research and are important omissions in the shorter age range analysis. Although it is beyond the scope of this paper, it is apparent that a more extensive analysis that includes more time period comparisons could further explicate the effects of differing lengths of follow-up on trajectory attributes by crime type.

[15] The mean group assignment probabilities for the incarceration analysis of total offending range from 88% to 94%.

[16] Again, the groups selected for comparison are those that best illustrate the issues at hand.

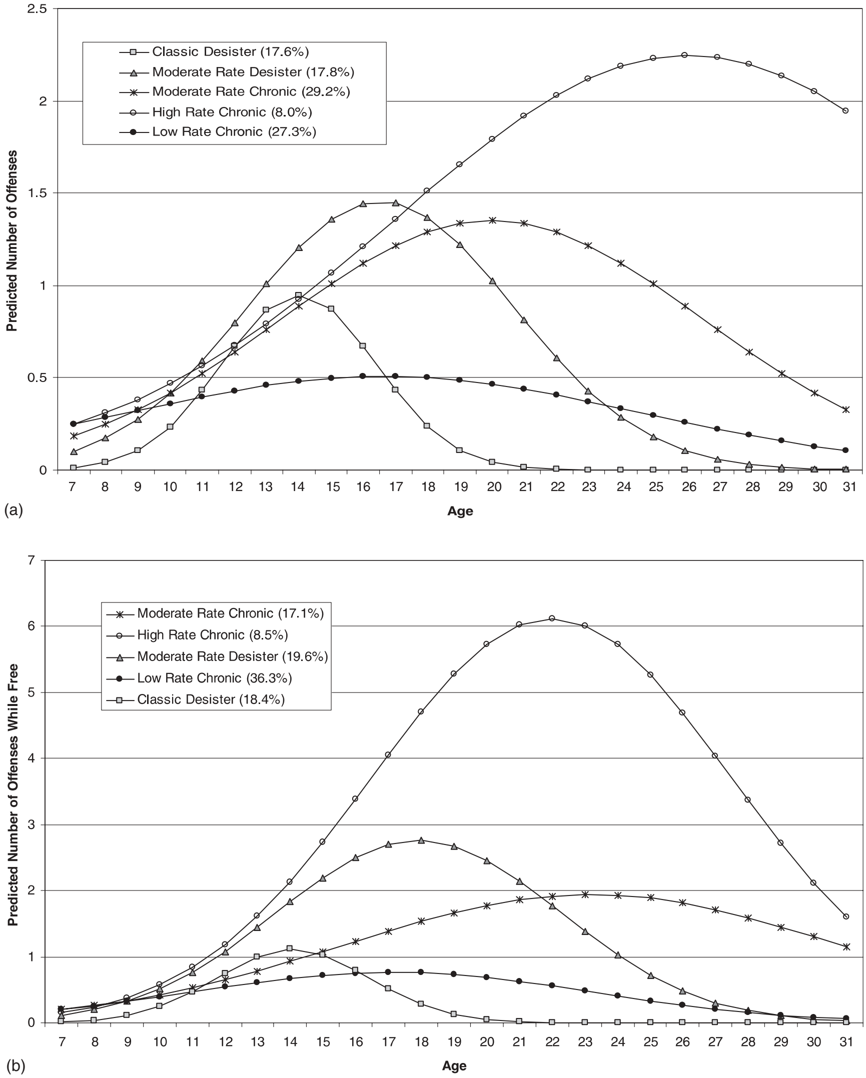

Fig. 6. Developmental trajectories of offending: without and with controlling for incarceration time.

without the incarceration parameter are also in this group when incarceration time is included. In other words, over 60% of the men are no longer identified as moderate-rate chronics once incarceration time is taken into account.

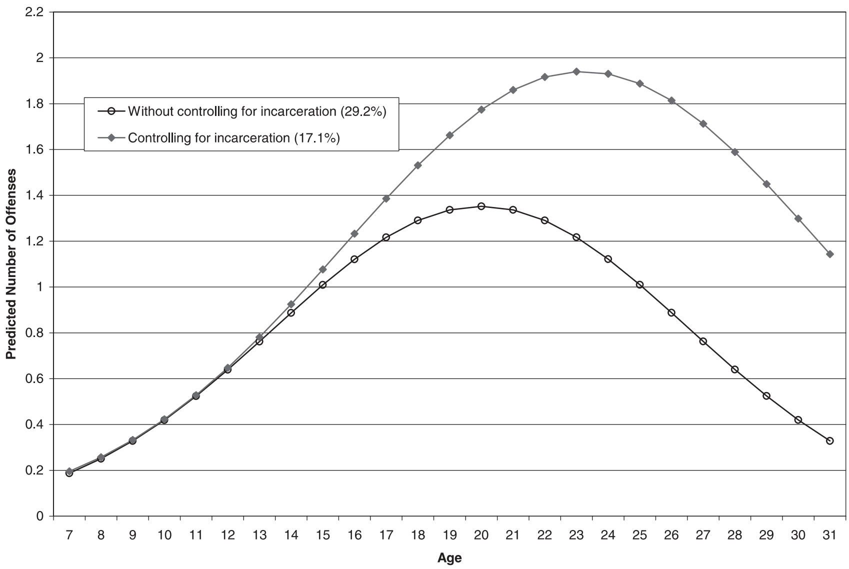

Fig. 7. Moderate-rate chronic offenders: a comparison of models with and without controlling for incarceration time.

In contrast, we see more consistency and stability with the classic desisters (Fig. 8). The peak age of offending is 14 regardless of whether incarceration is considered or not and there is considerably more stability in those assigned to that group. For these classic desisters there is little movement between groups as only 3% of the men move from the classic desister group to other groups in the model once incarceration time is taken into account. It is likely that these offenders are less affected by the omission of incarceration information since they desist from offending in their early twenties unlike the moderate-rate chronics who continue to offend throughout the sampling period and thus have a greater probability of being incarcerated.

Figure 9 shows the high-rate chronic group where the differences are the most dramatic. With incarceration time in the model, offending peaks in the early twenties at just over 6 offenses per year and slowly declines thereafter to 1.5 offenses per year by age 32. Without incarceration in the estimation, offending consistently increases into the early twenties before leveling off at approximately 2 offenses per year for the remainder of the time period. Stability in group membership shows that over half (56%) of the high-rate chronics in the model without the incarceration parameter are no longer classified as high-rate chronic offenders when incarceration is taken into

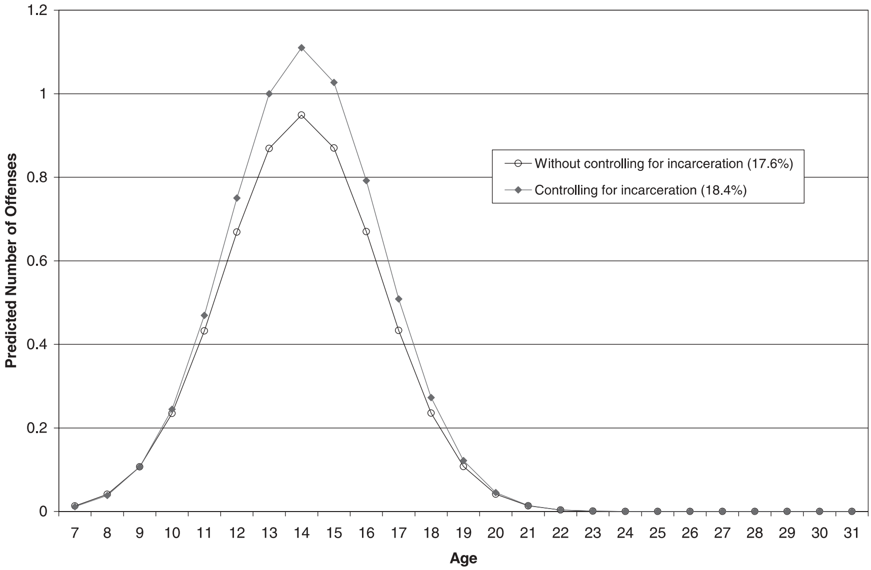

Fig. 8. Classic desister offenders: a comparison of models with and without controlling for incarceration time.

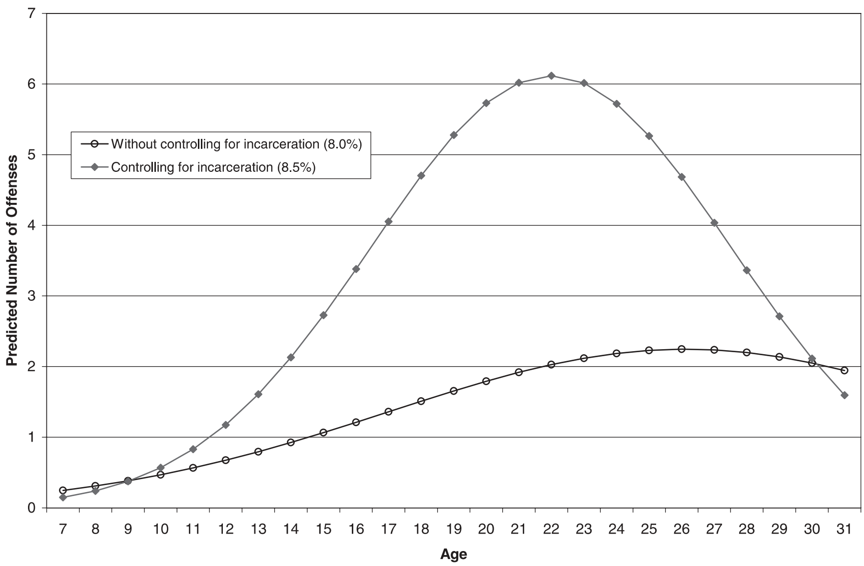

Fig. 9. High-rate chronic offenders: a comparison of models with and without controlling for incarceration time.

account. Again, this percentage is more similar to the moderate-rate chronics, pointing to the fact that these trajectory groups are the most affected by the inclusion of incarceration.[17]

From these analyses, we can conclude that the exclusion of incarceration time results in underestimating the rate of offending and can affect group shape, peak age, and group membership. In other words, the attributes of developmental trajectories using the semiparametric group-based approach are sensitive to the exclusion of incarceration time.[18] While not all groups show instability, the comparisons for the high-rate chronic group, which is frequently of theoretical and policy importance, do show some drastic differences. These results concur with Piquero and his colleagues (2001) in their finding that incarceration time is an important factor to consider when estimating trajectories and that it can substantially affect the attributes of developmental trajectories. This conclusion seems especially pertinent when studying serious persistent offending.

6.3. Mortality

Figure 10 shows the two estimated models, one without information on death (Fig. 10a) and one that integrates death information into the criminal offense histories (Fig. 10b).[19] Although an additional group is identified in the model that does not integrate death information, the comparison of group shapes, peak ages, and group membership show fairly similar patterns.

One exception to this statement is that the population of the high-rate chronic group is greatly affected by the exclusion of death information. When accounting for death, the high-rate chronic group has fifteen individuals assigned to that group. When death information is not incorporated, however, this number drops to six men, which is a loss of over 50% of the group's members. Therefore, when those who are dead are assumed to have desisted, the high-rate chronic group population is underestimated. More specifically, when death is integrated into the offense histories, seven of the nine additional people in the high-rate chronic group are, in fact, dead. These men

[17] Again, for the incarceration analysis, we replicated the group membership comparisons selecting on those with a group assignment probability of at least 0.90 in both models and found virtually identical results with those reported here.

[18] To investigate this issue further, six additional trajectory models were estimated using the semiparametric mixed Poisson model. These models are used to investigate the effects of incarceration time for property crime, violent crime, and alcohol and drug crime separately. All of the crime specific models again show the pattern of underestimating the rate of offending when incarceration time is excluded from the model, especially for the chronic offenders (data not shown).

[19] The mean group assignment probabilities for the mortality models range from 89% to 99.9%.

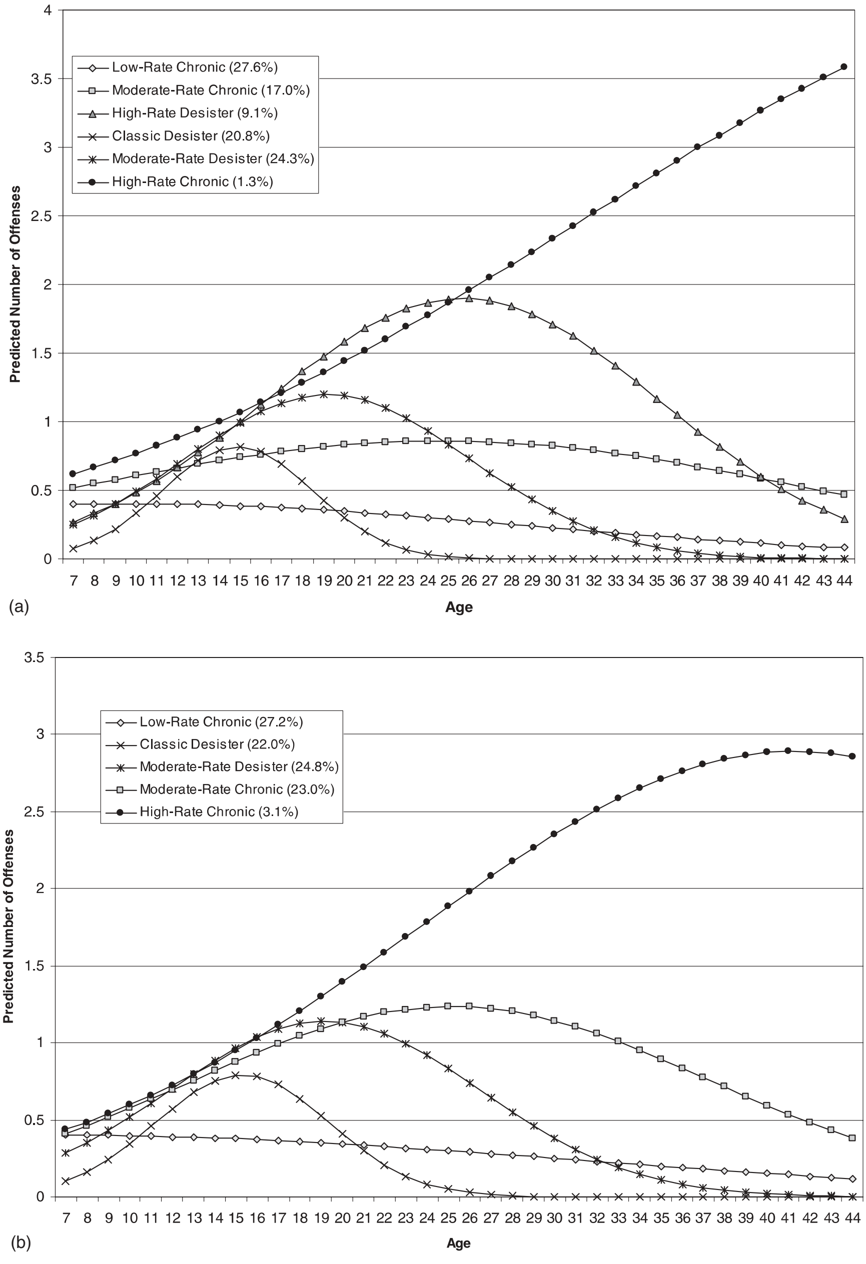

Fig. 10. Developmental trajectories of offending: without and with accounting for death.

were high-rate offenders when they were alive yet are assumed to have desisted when mortality is not integrated into the criminal histories. Not surprisingly, these seven men died between ages 24 and 42 and were placed in either the high-rate desister group or the moderate-rate chronic group when mortality was not taken into account.

This finding illustrates the problem of "false desistance" that emerges when death is not considered in the estimation of offending patterns over time (Reiss, 1989; Laub and Sampson, 2003). Consistent with research showing the linkage between serious delinquency and mortality (see Laub and Vaillant, 2000), the conclusion is that mortality information is important to include, especially when studying high-rate chronic offending. In addition, due to the increase in violence over the past few decades, a more contemporary sample may be even more affected by an exclusion of death information when assessing offending patterns over time.

7. DISCUSSION

The extant literature using group-based methods to estimate developmental trajectories suggests that there is a fair degree of consistency among and across samples with respect to group number and shape. One major issue that has not been addressed in the research is the consideration of length of follow-up and how length of follow-up may be affecting the results of these analyses. All of the previous literature has used a relatively short age range to estimate trajectories. The current research shows that length of follow-up influences trajectory patterns, suggesting that these effects should be explicitly considered when analyzing trajectories produced by the semiparametric group-based approach. It may be the case that identified groups based on the age range of 6 to 15 or 10 to 32 are not necessarily equivalent with respect to group shape, peak age, or group membership to those that would be identified if longer-term data were available. Another major issue is that incarceration and mortality information have been neglected in past research and need to be integrated into longitudinal trajectory analyses whenever possible, especially when considering serious persistent offending. In short, these considerations need to be acknowledged when employing the semiparametric group-based approach and researchers need to be cognizant of how length of follow-up, incarceration, and mortality information may affect their results with respect to trajectory groupings.[20]

[20] As mentioned in the introduction, the consequences of extrapolating beyond the support of the data and excluding incarceration and mortality information are not unique to the semiparametric group-based method. These issues are important when employing any longitudinal method, including the semiparametric group-based approach.

To take the implications of these findings one step further—understanding how these various conditions can affect the shape and population of each group is crucial once the analysis moves beyond the descriptive phase into the causal analysis stage. In most instances, identified trajectories are used to investigate theoretical issues such as how childhood, adolescent, or adult covariates are related to these groupings. If there are different members included in a trajectory group given different lengths of follow-up, for instance, this fact could potentially change the results of subsequent tests that are based on the characteristics of people in the identified trajectory groups.[21]

As the body of research using the semiparametric group-based approach grows, researchers also need to investigate other issues that may affect trajectory attributes. For instance, to what degree does the operationalization of the dependent variable affect trajectory groupings? Would an analysis that only includes the most serious offenses (i.e., violent and serious property offenses) show different results than when all offenses are included?[22] Does an analysis that uses self-report vs. official data change trajectory groupings? Finally, does the amount of time between data points affect trajectory groupings (i.e., annual assessments vs. assessments every three years)? These issues may be especially salient when comparing results using the trajectory method across different studies.

In sum, there is always a danger when a particular methodology approaches hegemonic status within a field of inquiry. At such a point questions are no longer asked and researchers unthinkingly apply the method of the day. Despite the popularity and apparent benefits of semiparametric methods of analyzing longitudinal criminological data, we believe researchers need to step back and assess how the method responds under varying data conditions. In this paper, we explored three such conditions—length of follow-up, incarceration time, and mortality. Our conclusion is that these data conditions do influence the results of the analysis, sometimes in major ways (i.e., among chronic offender groups).

Thus, we would encourage researchers to continue to conduct future sensitivity analyses of this method, as well as others. Recently, Bauer and Curran (2003) conducted an analysis of growth mixture models

[21] However, an analysis of the implications of these data conditions during the causal analysis stage is beyond the scope of this paper. Thus, this assertion remains a speculation in need of systematic analysis to verify or refute it.

[22] In the Glueck data, restricting the dependent variable to more serious offending (defined as violent, property, and drug or alcohol offenses only) for the length of follow-up analysis reveals similar results to those presented above. The primary difference between these two analyses is that when the outcome variable is confined to more serious offenses, the differences appear to be less severe.

(i.e., mixtures of normal distributions) which suggested that the latent-class identification of groups can be wholly arbitrary in non-normal data. More specifically, based on fit statistics of simulated data drawn from a non-normal distribution, these researchers found that a two class model was identified as the optimal model even though the population was homogeneous (one "true" group). While these findings technically do not derive from a direct application of the semiparametric mixed Poisson model, our analysis, in combination with Bauer and Curran's larger substantive point that statistical methods can misleadingly extract non-existent groups, suggests that caution is warranted along with sustained sensitivity analysis for all latent class analytical techniques.

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