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OVERVIEW OF A SEMI-PARAMETRIC, GROUP-BASED APPROACH FOR ANALYZING TRAJECTORIES OF DEVELOPMENT

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ABSTRACT

A developmental trajectory describes the course of a behavior over age or time. This paper will provide an overview lecture of a semi-parametric, group-based method for analyzing developmental trajectories. This methodology provides an alternative to assuming a homogenous population of trajectories as is done in standard growth modeling. Four capabilities will be described: (1) the capability to identify rather than assume distinctive groups of trajectories, (23) the capability to estimate the proportion of the population following each such trajectory group, (3) the capability to relate group membership probability to individual characteristics and circumstances, and (4) the capability to use the group membership probabilities for various other purposes such as creating profiles of group members. In addition, two important extensions of the method of will be described –the capability to add time-varying covariates to trajectory models and the capability to estimate joint trajectory models of distinct but related behaviors. The former provides the statistical capacity for testing whether a contemporaneous factor, such as an experimental intervention or a non-experimental event like pregnancy, deflects a pre-existing trajectory. The latter provides the capability to study unfolding of distinct but related behaviors such as childhood problem behavior and adolescent drug abuse.

1. INTRODUCTION

In this article I provide a brief, non-technical overview of my decade-long research program aimed at developing a group-based method for analyzing developmental trajectories. This work is more fully described, including technical details, in Nagin (1999) and Nagin and Tremblay (2001a). A comprehensive treatment is forthcoming in a book to be published by Harvard University Press. Also, a SAS-based procedure with the capability for supporting all of the analysis described in this overview is also available free of charge from the web site www.stat.cmu.edu/~bjones/. Documentation is also available at the site. For an overview of the software see Jones, Nagin, and Roeder (2001).

Longitudinal data provides the empirical foundation for research on wide-ranging topics in the social and behavioral sciences and in medicine. A few examples: psychologists and psychiatrists use longitudinal data to study the developmental course of psychopathologies, criminologists use longitudinal data to analyze the progression of delinquency and criminality over life stages, economists use longitudinal data to estimate models of income dynamics, sociologists use longitudinal data to study the evolution of the socioeconomic status of communities, and medical researchers use longitudinal data to study the progress of diseases and physiological processes.

The common statistical objective across these diverse application domains is modeling the progression of a phenomenon as it evolves over age or time. Over the past quarter century two main branches of methodology have evolved for the statistical analysis of growth processes: hierarchical modeling (Bryk and Raudenbush, 1987, 1992; Goldstein, 1995), and latent curve analysis (McArdle & Epstein, 1987; Meredith and Tisak, 1990; Muthen,1989; Willett and Sayer, 1994). While these two classes of models differ in important respects, they also have important commonalities (MacCallum, Kim, Malarkey, Kiecolt-Glaser, 1997; Willett & Sayer, 1994; Raudenbush, 2001). For the purposes of this paper one is key: both model the unconditional and conditional population distribution of growth curves based on continuous distribution functions. Unconditional models estimate two key features of the population distribution of growth curves parameters—their mean and covariance structure. The former defines average growth within the population and the latter calibrates the variances of growth throughout the population. The conditional models are designed to explain this variability by relating growth parameters to one or more explanatory variables.

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In this overview I describe a distinct semi-parametric, group-based approach for modeling developmental trajectories. As described in Nagin (1999) and Nagin and Tremblay (2001), the method is based on finite mixture modeling. Its application to a Montreal-based data set is illustrated in Figure 1. Specifically, this data is a product of a study that tracked 1037 white males of French ancestry. Subjects were selected in 1984 from kindergarten classes in low socioeconomic Montreal neighborhoods. Following the assessment at age 6, the boys and other informants were interviewed annually from ages 10 to 17. Assessments were made on a wide range of factors. Among these were self reports by the boy of whether or not he had been involved with a delinquent gang in the past year.

As reported in Lacourse et al. (forthcoming), application of the group-based method to this gang involvement data identified the three highly distinct groups shown in Figure 1. The trajectory for each group is described by the probability of gang membership at each age: One was a large group, estimated to comprise 74.4% of the population, whose probability of gang membership was very small over all ages. The second group, called the childhood onset group, started with a high probability of gang membership at age 11 that rose modestly till age 14 and then declined thereafter. The third group, called the adolescent onset group, started off with a near-zero probability of gang membership at age 11, but thereafter rose to a rate that actually exceeded that of the childhood onset group. The method estimates that the latter two groups each constitute 13.4% of the sampled population.

The essence of the motivation for the group-based method is captured in a late 19th century temperance print. The left side of the print depicts a socially and personally productive life course. The first panel shows an earnest boy, book in hand, walking to school. In the second panel, the boy is now a young man with his wife and child lovingly looking on as he is hard at work. In the third panel, the focal character is now an old man sitting in a garden with the family of his grown child. The right side depicts a socially counterproductive, and personally destructive, life course. In the first panel, the boy is drinking and carousing with his mates; in the second, he is abusing his wife in a drunken rage; and in the final panel, he is at hard labor in prison. Minus the Victorian moral undertones of this print, the group-based methods is designed to identify such distinctive life trajectories and provide a statistical basis for uncovering the forces that propel people down these very different life paths.

Raudenbush (2001:59) describes the group-based approach as a "multinomial" modeling strategy and offers valuable insight into an important class of problems for which a group-based approach is particularly appropriate. For some developmental problems it is reasonable to assume that all individuals either increase or decrease according to a common growth process. He offers language acquisition as a quintessential example. Another good example is time spent with peers from childhood through adolescence (Warr, 2001). Conventional growth curve methods are well suited for analyzing such developmental phenomena. However, there are large classes of problems for which growth curve models do not naturally fit. Raudenbush uses depression as an example. He observes: "It makes no sense to assume that everyone is increasing (or decreasing) in depression...many persons will never be high in depression, others will always be high, while others will become increasingly depressed." For this class of problems he recommends the group-based approach that is the subject of this book.

The basis for Raudenbush's distinction between the developmental processes underlying language acquisition and depression is fundamental. Because the vocabularies of all young children from normal populations increase with age, it is sensible to ask the questions such as: What is the average growth curve of children' vocabulary over a specified age range? How large is the variation across children in their individual-level language acquisition growth curves? How do such between person variations relate to factors such as the child's cognitive functioning and parental education? How are within person changes in acquisition related to changes in interactions with primary caregivers due, for example, to parental conflict?

These questions are framed in the language of analysis of variance as reflected in the use of terms such as "within person changes" and "between person changes". This is only natural because conventional growth curve analysis has its roots in analysis of variance. Like analysis of variance, growth curve analysis is designed to sort out factors accounting for variation about a population mean. It also adopts the normality assumption which is the cornerstone of analysis of variance. Specifically, growth curve analysis assumes that individual level growth parameters are normally distributed in the population.

Framing a statistical analysis of a time varying process in the conceptual apparatus of analysis of variance requires that it be sensible to characterize population differences in a phenomenon in terms of variation about its mean time trend. For processes like language acquisition the mean trend is, in fact, is a sensible statistical anchor for describing

individual variability. However, for many processes evolving over time or age, it is not. Returning to the depression example, it makes no sense to frame a statistical analysis of population differences in the developmental progression of depression in terms of variation about a mean "trajectory of depression." Other examples of evolving behavioral phenomena that are not properly described in terms of variation about a population mean are most forms of psychopathology, smoking, drinking, and illicit drug use. More generally a group-based approach to analyzing repeated measure data is usefully applied to phenomenon in which there may be qualitatively different trajectories of change over age or time across subpopulations that are not identifiable ex ante based on some measured characteristic such gender or race.

2. OTHER RATIONALES FOR A GROUP-BASED STATISTICAL MODEL

There is a long tradition in developmental psychology of group-based theorizing about both normal and pathological development. Examples include theories of personality development (Caspi, 1998), drug use (Kandel, 1975), learning (Holyoak and Spellman, 1993), language and conceptual development (Markman, 1989), depression (Kasen et al., 2001), eating disorders (Tyrka et al., 2000), anxiety (Cloninger, 1986), and the development of prosocial behaviors such as conscience (Kochanska et al., 1997) and of antisocial behaviors such as delinquency (Loeber, 1991; Moffitt, 1993; Patterson, DeBaryshe, and Ramsey, 1989).

Because conventional growth curve modeling methods are ill-suited to their needs, developmental researchers have commonly resorted to using assignment rules based on subjective categorization criteria to construct categories of developmental trajectories. For example, Haapasalo and Tremblay (1994) propose a taxonomy comprised of five groups—stable high fighter, desisting high fighters, late onset high fighters, variable high fighters, and nonfighers. The groups were created based on assessments of physical aggression spanning a period from age 6 to 12 in the previously described Montreal-based longitudinal study. In this study, subjects were scored each assessment period on a three-item scale of physical aggression: kicking, biting, and hitting other children; fighting with other children; and bulling and intimidating children. See Tremblay et al., (1987) for further details on this study. Haapasalo and Tremblay labeled boys who scored high on this scale for any any given period as a "high fighters" for that period. They then defined rules for assigning individuals into the five-group taxonomy. These rules were based on the frequency and trend of each boy's classification as a high fighter. For example, desisting high fighters were boys who were high fighters in kindergarten but who were classified as high fighters in no more than one of the ensuring assessment periods.

Moffitt's (1993) well-known taxonomy is more parsimonious. She posits only two distinct developmental trajectories of problem behavior. One group follows what she calls a life course persistent (LCP) trajectory of antisocial behavior and the other group is posited to follow an adolescent limited (AL) trajectory. In empirical tests of her theory (e.g., Moffitt, 1996) she uses classification rules that are conceptually similar to those used by Haapasalo and Tremblay. LCPs are defined as individuals who score one or more standard deviation above the mean in three of four assessments of a conduct disorder index between the ages 5 & 11 and who also score at least one standard deviation above the mean in self reported delinquency at least once at either age 15 or 18. The ALs are defined as individuals who do not meet the LCP criterion for childhood conduct problems but who do achieve the LCP threshold for adolescent delinquency.

While such assignment rules are generally reasonable, there are limitations and pitfalls attendant to their use. One is that the existence of distinct developmental trajectories must be assumed a priori. Thus, the analysis can not test for their presence, a fundamental shortcoming. A second and related pitfall is the risk of simultaneously "over- and under-fitting" the data by creating trajectory groups that reflect only random variation, and failing to identify unusual but still real developmental patterns. Third, ex ante specified rules provide no basis for calibrating the precision of individual classifications to the various groups that comprise the taxonomy. That is, the uncertainty about an individual's group membership cannot be quantified in the form of probabilities with associated confidence intervals.

To illustrate these limitations, consider the Haapasalo and Tremblay (1994) study. Figure 2 displays the results of an application of the group-based method to the same Montreal-based data set used in that analysis. Specifically, the method was applied to annual assessments of physical aggression made at age 6 and again at age 10 to 15. The application, which was first reported in Nagin and Tremblay (1999), found that a four-group model best fitted the

data. A group called “lows” is comprised of individuals who display little or no physically aggressive behavior. This group is estimated to comprise about 15% of the sample population. A second group, that comprises about 50% of the population, is best labeled “moderate decliners.” At age 6, boys in this group displayed modest levels of physical aggression, but by age 10 they had largely desisted. A third group, comprising about 30% of the population, is labeled “high-level decliners.” This group starts off scoring high on physical aggression at age 6, but scores far lower by age 15. Notwithstanding this marked decline, at age 15 they continue to display a modest level of physical aggression. Finally, there is a small group of “chronics,” comprising about 5% of the population, who display high levels of physical aggression throughout the observation period.

The Nagin and Tremblay analysis provides formal statistical support for the presence of three of the groups hypothesized in the Haapasalo and Tremblay taxonomy: the stable high fighters who correspond to the chronic trajectory group; the desisting high fighters who correspond to the high declining trajectory group; and the lows, who correspond to the nonfighters. However, there is no evidence of a trajectory corresponding to the late onset high fighter group or of a variable high fighter group. These are examples of classifications that are likely over-fitting the data by creating groups that are confounding random variation with real structural differences. There also seems to be evidence of the under-fitting problem. The taxonomy fails to identify the moderate declining trajectory group. In Nagin and Tremblay (1999) and Nagin et al. (forthcoming) the moderate declining group is found to be distinctive in some respects from the low physical aggression trajectory group.

Two other examples of the utility of the formal group-based trajectory method compared to ad hoc classification procedures are studies by Nagin, Farrington, and Moffitt (1995) and Lacourse, et al. (forthcoming). The former application was intended to test several predictions of Moffitt’s taxonomic theory. One was to test for the very presence of the trajectories predicted by the taxonomy. Based on an analysis of data convictions from age 10 to 32 in a sample of 403 males from a poor neighborhood in London, England, three offending trajectories were found. The trajectories are shown in Figure 3. One trajectory, which peaks sharply in late adolescence, closely matches the adolescent limited group predicted by the theory. The high hump shaped trajectory is similar in some respects to Moffitt’s life course persistent group. The group is already actively engaged in delinquency at age 10. However, their frequency of antisocial behavior, at least as measured by conviction, is very age dependent—a pattern that is not anticipated by Moffitt’s theory. It rises until about age 18 and then begins a steady decline. By age 30 it has dropped below its starting point at age 10 and is about equal to the rate of a third group called low rate chronic offenders. This final group was not included in Moffitt’s taxonomy. Thus, this application of the group-based method provided basic confirmation of the presence of the AL and LCP trajectories that Moffitt predicts in her taxonomy but also suggests that the LCP trajectory may be more age dependent than anticipated by the theory. Further, the low rate chronic trajectory was not predicted by the taxonomy.

The Lacourse et al. (forthcoming) analysis reported in Figure 1 illustrates two other valuable properties of the group-based modeling approach compared to the use of classification rules. One is the capacity to identify qualitatively distinct developmental progressions that are not readily identifiable using ad hoc, ex-ante classification rules. In principle the childhood onset and adolescent onset groups are identifiable ex-ante, but given their specific developmental courses it would be very difficult to distinguish them from chance variation without a formal statistical methodology. A second closely related advantage stems from the use of a statistical structure. It is because of this structure that the methodology has the capacity for distinguishing chance variation across individuals from real differences and for calibrating whether within individual change is real or only random variation. Because the child and adolescent onset trajectories are the product of a formal statistical model, there is a firmer basis for their reality than if they had been constructed based on subjective classification rules.

The group-based methodology is also responsive to appeals for the development of “person-based” approaches to analyzing development (Bergman, 1998; Magnusson, 1998). Such appeals are motivated by a desire for methods that can provide a statistical snapshot of the distinguishing characteristics and behaviors of individuals following distinctive developmental pathways. The group-based method lends itself to creating such profiles.

This capacity is illustrated by the summary statistics reported in Table 1 that profile of the characteristics of individuals following the four physical aggression trajectories shown in Figure 2. After trajectories are estimated, the model’s parameter estimates can be used to calculate the probability of an individual belonging to each of the trajectory groups. To create the profiles reported in Table 1, individuals were assigned to the trajectory group in which they mostly likely belonged based on their measured history of physical aggression. The summary statistics

reported in the table are simply the product of cross-tabulations of group membership so defined with the various individual characteristics and outcomes reported in the table.

The profiles conform to longstanding findings on the predictors and consequences of problem behaviors such as physical aggression. The chronics have the least educated parents and most frequently score in the lowest quartile of the sample's IQ distribution. By contrast, the nevers are least likely to suffer from these risk factors. Further, 90% of the chronics fail to reach the eighth grade on schedule and 13% have a juvenile record by age 18. In comparison, only 19% of the nevers have fallen behind by the eighth grade and none have a juvenile record. In between are the low- level and high-level decliners.

Table 1 demonstrates that trajectory group membership varied systematically with individual characteristics as well as circumstances, such as parental education that pre-date measurement series. An important generalization of the base model allows for joint estimation of both the shapes of the trajectory groups and also the impact of various psycho-social characteristics on the probability of trajectory group membership. This extension, which is described in Nagin (1999) and Roeder, Lynch, and Nagin (1999), provides the capability for identifying and testing early predictors of long run patterns of behavior. For example, such an analysis shows that the probability of trajectory group membership is significantly predicted by low IQ, low paternal education, and being born to a mother who began child-bearing as a teenager (Nagin and Tremblay, 2001b).

Two other important extensions of the basic model are important to note. One, which is elaborated in Nagin et al. (in press) , provides the capacity for obtaining *trajectory group-specific estimate*s of whether and to what degree a turning point event, such as being held back in school, an intervention like counseling, or an ecological factor such as changing neighborhood poverty, alters the developmental course of the behavior under investigation. Figure 4 illustrates this extension. It is the product of a statistical analysis reported in Nagin et al. (in print) that examines the influence of grade retention on physical aggression for each of the trajectory groups depicted in Figure 2. Statistically significant impacts were found only for the two middle groups. Figure 4 depicts the results of the model for the moderate declining trajectory group. The results show that the impact of grade retention seems to depend on age: retention at ages 6 to 10 has approximately the same aggravating influence on physical aggression as retention at ages 11 to 12, while retention from age 13 to 15 seemingly has no material influence.

The second major extension involves the capacity for estimating joint trajectory models. Two prominent themes in developmental psychology, developmental psychopathology, and developmental criminology are comorbidity and heterotypic continuity. Comorbidity refers to the contemporaneous occurrence of two or more undesirable conditions, such as conduct disorder and hyperactivity during childhood or anxiety and depression in adulthood. Heterotypic continuity is the manifestation over time of a latent individual trait in different but analogous behaviors.

Comorbidity and heterotypic continuity are typically represented by a single summary statistic, usually a correlation or odds ratio, that either measures the co-occurrence of the two behaviors or symptoms of interest (e.g., hyperactivity and conduct disorder at age 6) or, alternatively, relates the two distinct behaviors measured at different life stages (e.g., physical aggression at age 5 and violent delinquency at age 15.) In Nagin and Tremblay (2001a), we develop and demonstrate an extension of the group-based model that relates the entire longitudinal course of the two behaviors of interest. The generalization provides the capacity for the joint estimation of trajectory models for two distinct, but theoretically related, measurement series. Three key outputs of the model are: (1) the form of the trajectory of distinctive sub-populations for both measurement series, (2) the probability of membership in each such trajectory group, and (3) the joint probability of membership in trajectory groups across behaviors. This final output is the key advance of the joint model, which offers two novel features. First, the joint probabilities can characterize the linkage in the developmental course of distinct but related behaviors. Second, the joint probabilities can measure differences within the population in the form of this linkage.

The aim of this article was to provide a non-technical overview of my work program on group-based trajectory modeling. Much work remains to be done. Perhaps the most important is to provide the capacity for taking account of the possibility that turning-point events, such as school failure, or treatments, such as counseling, may be both a cause and effect of the behavior under study. Still another important issue is developing firm guidelines for making well-informed judgments on the optimal number of groups to create. While much more work is required to develop the method to its fullest potential, I now feel confident in judging it a valuable addition to the statistical tools available for the study of trajectories of development.

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Table 1: Physical Aggression Group Profiles

Variable	Group			
	Never	Low Desister	High Desister	Chronic
Years of School – Mother	11.1	10.8	9.8	8.4
Years of School – Father	11.5	10.7	9.8	9.1
Low IQ (%)	21.6	26.8	44.5	46.4
Completed 8th Grade on Time (%)	80.3	64.6	31.8	6.5
Juvenile Record (%)	0.0	2.0	6.0	13.3
# of Sexual Partners at Age 17 (Past Year)	1.2	1.7	2.2	3.5

Figure 1: Trajectories of Gang Membership

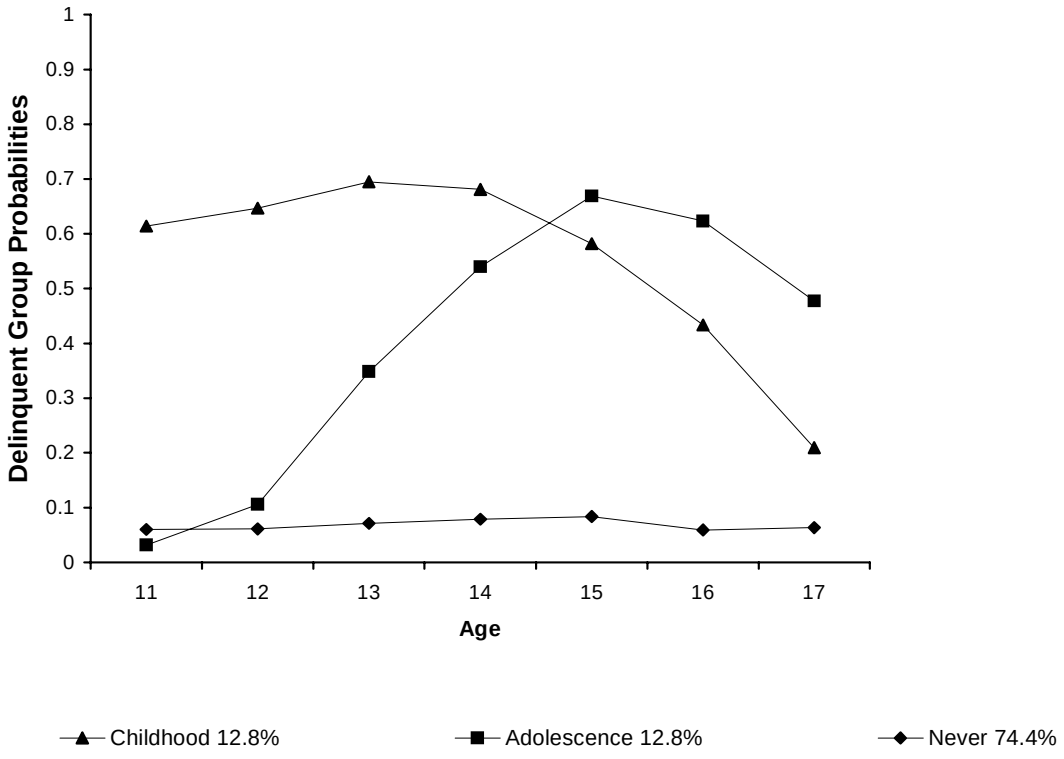

Figure 2: Trajectories of Physical Aggression

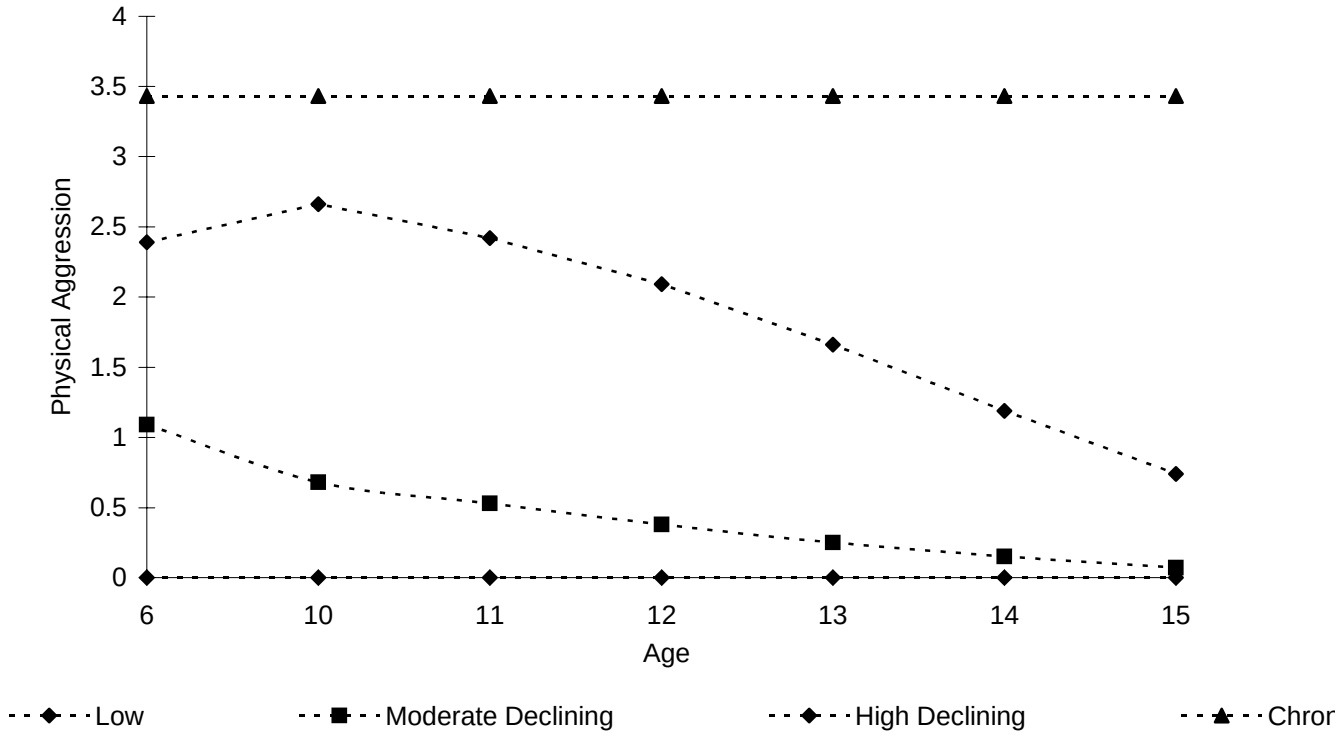

Figure 3: Trajectories of Convictions

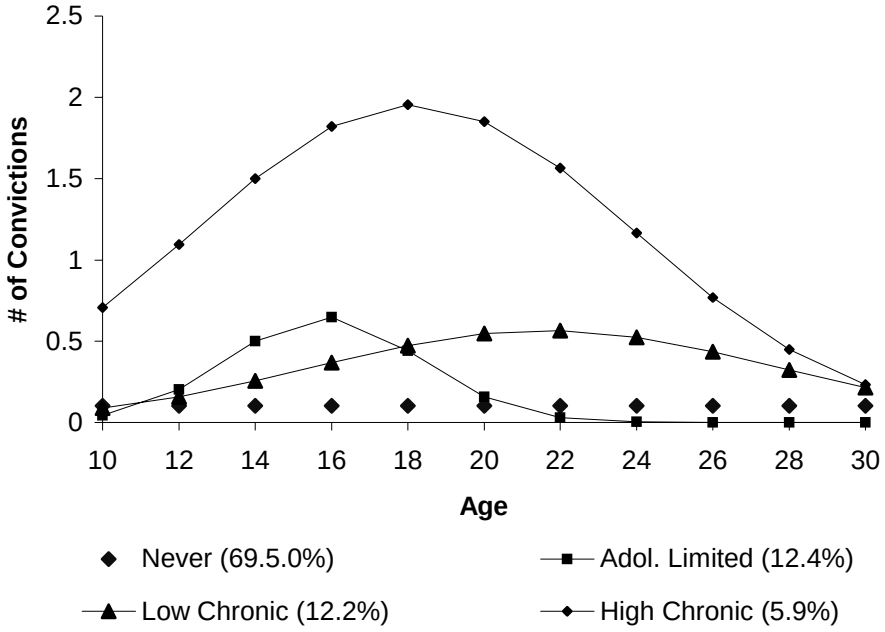

Figure 4: School Retention Impacts: Moderate Decliner Trajectory