ABSTRACT

Title of Dissertation: THE IMPLICATIONS FOR DESISTANCE OF THE DEVELOPMENTAL COURSE OF CHILDHOOD AGGRESSIVE BEHAVIOR

Sarah Nicholson Bacon, Doctor of Philosophy, 2006

Dissertation directed by: Professor Hanno Petras, Ph.D.
Department of Criminology and Criminal Justice

One of the most important goals for criminological research is to further our understanding of the concept of desistance. Challenges in defining and measuring desistance have been exacerbated by the lack of theoretical foundations to guide inquiry and empirical research. To date, only a few predictors have been empirically identified, and all of them are exclusively relevant to adulthood. An important objective for desistance research, then, is to identify factors associated with earlier desistance. This research endeavors to meet this objective by specifying a conceptual model relating the developmental course of early childhood aggression to offending behavior during adolescence and early adulthood. The relationships proposed by the conceptual model are assessed using a longitudinal measure of aggression and analytic techniques designed to assess change in development over time. An additional extension of existing research is the comparison of these relationships for boys and girls.

Data come from Johns Hopkins University's Prevention Intervention Research Center's school-based interventions trials in Baltimore City Schools. Participants comprise an epidemiologically defined sample of urban, primarily African-American, first grade boys and girls. Results suggest that some pathways to desistance may be identified before adulthood, thus supporting the notion that examinations of early development have utility for informing our understanding of later processes.

THE IMPLICATIONS FOR DESISTANCE OF THE DEVELOPMENTAL COURSE OF CHILDHOOD AGGRESSIVE BEHAVIOR

by

Sarah Nicholson Bacon

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Advisory Committee:

Professor Hanno Petras, Chair
Professor Shawn D. Bushway
Professor John H. Laub
Professor Ray Paternoster
Professor Seth Sanders

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TABLE OF CONTENTS

List of Tables

List of Figures

List of Abbreviations

AL	Adolescence Limited
ALRT	Adjusted Likelihood Ratio Test
BPP	Baltimore Prevention Project
BIC	Bayesian Information Criterion
BLRT	Bootstrapped Likelihood Ratio Test
CFI	Comparative Fit Index
CGM	Conventional Growth Model
CI	Confidence Interval
DF	Degrees of Freedom
GMM	Growth Mixture Model
GGMM	General Growth Mixture Model
HD	High-Declining
HLM	Hierarchical Linear Modeling
HOR	Hazard Odds Ratio
I	Intercept
IS	Intercept-Slope
ISQS	Intercept-Slope-Quadratic Slope
ITD	Interactional Theory of Delinquency
LCGA	Latent Class Growth Analysis
LCP	Life-Course Persister
LI	Low-Increasing
LL	Log Likelihood
LMR	Lo Mendell Rubin
LS	Low Stable
MAR	Missing At Random
MGA	Multiple Groups Analysis
MI	Moderate-Increasing
MIMIC	Multiple Indicator Multiple Causes
MS	Moderate-Stable
OR	Odds Ratio
PIRC	Prevention Intervention Research Center
RMSEA	Root Mean Square Error of Approximation
SE	Standard Error
SPGM	Semi-Parametric Group-based Modeling
SRMR	Standardized Root Mean Square Residual
SSABIC	Sample Size Adjusted Bayesian Information Criterion
TLI	Tucker Lewis Index
TOCA-R	Teachers Observations of Classroom Adaptation - Revised

CHAPTER ONE: INTRODUCTION

One of the most important goals of criminological inquiry is to gain an understanding of the developmental process of desistance, which eventuates in the ultimate arrival at a state of nonoffending (Brame, Bushway and Paternoster, 2003; Bushway, Thornberry and Krohn, 2003; Laub and Sampson, 2003). Indeed, from a practical policy perspective, it may be argued that understanding desistance – and therefore gaining insight as to how to foster it – is second only to preventing the onset of criminal behavior. Early desistance research confronted unique challenges in operationalizing, measuring, and modeling desistance, and the lack of explicit theoretical guidance exacerbated the issue. To date, these challenges have been met with a fair degree of success, and a nascent theoretical literature has emerged. Recent desistance research has made tremendous progress in furthering our understanding of this developmental process, yet many unanswered questions remain. Relatively little is known about the causes or predictors of desistance, and the focus of research rarely extends beyond limited operationalizations of desistance from offending in adulthood. As a consequence, the few predictors of desistance that have been identified and empirically supported are also specific to adulthood. If desistance were to be observed earlier in the life course, the benefits for crime prevention and public safety, both financial and holistic, would be considerable. An important objective for desistance research, then, is to identify factors associated with earlier desistance. This research

endeavors to meet this objective, first by specifying a conceptual model relating the developmental course of early childhood aggression and several theoretically derived predictors to a host of juvenile offending outcomes. This developmental progression is then related to a measure of adult offending. The relationships between childhood development and offending outcomes at each developmental stage are assessed to determine the extent to which the specified childhood risk factors vary systematically with offending and non-offending outcomes. An additional extension of existing research is the comparison of these relationships for boys and girls.

Sampson and Laub's Age Graded Theory of Informal Social Control

The body of work generated by Sampson and Laub, particularly as outlined in their seminal books *Crime in the Making: Pathways and Turning Points Through Life* (1993) and *Shared Beginnings, Divergent Lives (*Laub and Sampson, 2003; see also Laub and Sampson, 1993; Sampson and Laub, 1990, 1992), has made an immeasurable contribution to our understanding of desistance. Their longitudinal analysis of the Glueck data on five hundred delinquent boys reveals that, despite the notable and well-established continuity of antisocial behavior, behavioral change can occur at any point in the life course. This finding serves as an important deterrent for those who would misinterpret the continuity of antisocial behavior as synonymous with the immutability of trajectories of problem behavior. Sampson and Laub offer their Age-Graded Theory of Informal Social Control to account for both continuity and change. According to their

theoretical model (which enjoys considerable empirical support), the informal social control resulting from social bonds in adulthood – particularly bonds to employment and to a spouse – explains desistance from crime in adulthood independent of juvenile delinquency and other childhood risk factors. Thus has been established the central component of our understanding of desistance; that proximal adulthood influences in the form of social bonds explain the behavioral change in persistent offenders that is desistance. Consideration of this important finding motivates the question: What explains the development of adult social bonds? Sampson and Laub anticipate this question, and in response they assert that adult social bonds develop (or not) through the interaction of human agency, structural context, and the state-dependent effects of prior development and behavior. Ultimately, Sampson and Laub's work solidifies the place of adult social bonds in discussions of desistance, but their assertion that these bonds are largely influenced by pre-adult development highlights the need for further examination of the influence of early childhood factors.

Identifying the Early Roots of Desistance

While Sampson and Laub's model acknowledges the theoretical importance of childhood risk for later offending behavior, its practical application is limited to adulthood. That is, the social institutions they identify for their role in desistance are relevant only for adults. Certainly none would argue that stable employment and marriage are likely to induce desistance in children or juveniles. However, a central tenet

of the life course and developmental paradigms is that the antecedents of adult development are found in early childhood (Pulkkinen and Caspi, 2002; Robins, 1966). Thus, a continued (though not exclusive) focus on childhood still holds significant potential for illuminating the pathways from childhood development to desistance from offending, with consideration for the intervening adolescent development and offending that must precede desistance. To that end, this dissertation examines the influence of the developmental course of early childhood aggression on juvenile and adult offending and the implications of this relationship for later desistance from offending.

Early aggression is selected as the childhood risk of interest because it is the single best behavioral predictor of delinquency for boys (Farrington, 1986, 1989, 1991, 1994; Haapsalo and Tremblay, 1994; Reiss and Roth, 1993; Tremblay, Masse, Perron, LeBlanc, Schwartzman and Ledingham, 1992; Wasserman, Keenan, Tremblay, Coie, Herrenkohl, Loeber and Petechuk, 2003) and of violent delinquency in particular (Broidy, Nagin, Tremblay, Bates, Brame, Dodge, Fergusson, Horwood, Loeber, Laird, Lynam, Moffitt, Pettit and Vitaro, 2003; Hawkins, Herrenkohl, Farrington, Brewer, Catalano, Harachi and Cothern, 2000; Nagin and Tremblay, 1999). Childhood aggression is also strongly related to a multitude of other negative life outcomes such as school dropout, substance use, mental health challenges, and poor parenting (Cairns, Cairns and Neckerman, 1989; Petras, Schaeffer, Ialongo, Hubbard, Muthén, Lambert, Poduska and Kellam, 2004; Tremblay, Nagin, Séguin, Zoccolillo, Zelazo, Boivin, Pérusse and Japel, 2004). Thus, early childhood aggression evinces sufficient continuity[1] to motivate

[1] Researchers have offered two primary explanations for this finding of the continuity of behavior over time: persistent heterogeneity and state dependence (see Nagin and Paternoster, 1991, 2000 for a complete description). Persistent heterogeneity theories posit that individuals differ in their underlying criminal propensity, and these differences are relatively stable over time. Observed differences in antisocial

questions as to its influence on later offending. Importantly though, recent research on dynamic patterns of early aggression and their relationship with subsequent behavior forces the recognition that notable discontinuity emerges as well. This suggests that an examination of the development of aggression is relevant to both continuity and change.

Thornberry's Interactional Theory of Delinquency

Thornberry's Interactional Theory of Delinquency (ITD) (1987; Thornberry, Lizotte, Krohn, Farnworth and Jang, 1991) provides a theoretical template of sorts for this examination of the developmental progression of behavior over time – from childhood aggression to juvenile offending, to adult offending and finally to desistance. Thornberry points out that adolescence is the obvious developmental stage of focus for many theories of delinquency because that is when offending behavior is most likely to occur. When the focus on adolescence is exclusive, however, the causal influence of the preceding developmental patterns is ignored. Applying this line of reasoning to theories of desistance, then, if our goal is to explain desistance, we must look beyond the developmental period in which desistance is most likely (adulthood), and include consideration of earlier developmental periods (childhood and adolescence). With respect to the specific causal mechanisms at work in ITD, Thornberry posits that pathways in and out of antisocial behavior are shaped by the interaction of parents, schools, and peers, and that the influence of this interaction is structured by social context. Based on these theoretical propositions, then, a comprehensive understanding of

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behavior are a reflection of this underlying propensity, so the aggressive child who also drops out of high school and struggles with stable employment does so because of the same underlying causal propensity. State dependence theories, on the other hand, posit a causal influence of past behavior on future behavior, such that childhood aggression serves to increase the probability of future antisocial behavior, and the likelihood of prosocial behavior is attenuated.

the developmental periods antecedent to desistance requires tracing developmental patterns back as far as possible so that the influence of parents, teachers and peers may be assessed.

Taken together, the contributions of Sampson and Laub and of Thornberry demonstrate that behavioral change (specifically, desistance) can happen at any time and is explained by proximal social bonds. The presence or absence of these social bonds and the structural contexts in which they operate are explained by the preceding developmental periods. This synthesis of Sampson and Laub's and Thornberry's theoretical models provides the basis inferring a causal relationship between childhood development and desistance from offending in adulthood. The existence of a causal relationship is further suggested by the empirical literature, which clearly establishes that early childhood aggression is significantly associated with high school dropout, which is in turn associated with diminished opportunities for rewarding employment. To be clear, data constraints do not allow this proposed relationship to be explicitly modeled and tested with this research. However, relating patterns of early childhood development to concordant and discordant outcomes in adolescence and adulthood can provide an indication of desistance. Nor is this an explicit test of the theoretical propositions of Sampson and Laub or Thornberry. Their theoretical contributions simply provide an important foundation from which to build the conceptual model to account for the role of early patterns of aggression in shaping the timing and rate of later desistance.

Aggression, Desistance, and Gender

The literature on longitudinal patterns of aggressive behavior reflects a focus on the aggressive behavior of boys, so the dearth of research on the process of desistance for females is not surprising. The relative inattention to females in criminological research is driven, in part, by the modeling constraints and power limitations attendant to females' low base rates of involvement in antisocial behavior. However, some have taken females' lower rates of involvement in offending as substantive justification for ignoring them and focusing on the portion of the population that accounts for the bulk of offenses – males. As the gender gap in offending continues to narrow, this reasoning needs to be reassessed (Bureau of Justice Statistics, 1999; Hipwell, Loeber, Stouthamer-Loeber, Keenan, White and Kroneman, 2002; Tatem-Kelly, Huizinga, Thornberry and Loeber, 1997). Perhaps more compelling is the evidence that girls' trajectories of childhood aggression are similar to boys' in many respects, and yet girls go on to experience markedly different adolescent outcomes. This observation suggests greater stability and continuity of antisocial behavior for boys than for girls (Hawkins et al, 2000), and girls' low rates of offending should be viewed as cause for further scrutiny rather than cause for dismissal. What is it about girls that seems to allow more "vulnerability" to desistance? A better understanding of girls' patterns of antisocial behavior development will inform our understanding of the developmental progression of antisocial behavior more generally.

Summary of Research Aims and Significance of Research

Desistance research is at the fore of current criminological dialogue and attention, and this focus is warranted. Advancing our understanding of the process of desistance is essential for theory development, for applications of prevention and intervention practices, and for informing the policy writers and agencies responsible for disseminating these practices. This dissertation contributes to the growing body of desistance research in several ways. First, although many childhood factors have been empirically linked to juvenile offending, none have been linked explicitly with desistance. A conceptual framework for systematically analyzing the progression of development from childhood through adolescence, and finally to adulthood is presented here which allows for the influence of all antecedent development, such that the indirect effects of childhood factors can be assessed. Second, this research addresses the exigent need for research on females' development and the implications of their early development for later persistence or desistance. In addition, beyond the inclusion of females, the epidemiologically defined sample of urban elementary school children is unique to desistance research, and arguably represents a more relevant population for research with prevention implications in that, while the sample was not *selected* as a high-risk sample, it nevertheless *is* a high-risk sample. The potential implications of this research for prevention are profound: it is axiomatic to the developmental perspective that early identification of risk is preferred, as less ingrained behaviors are more easily redirected. Knowledge of childhood predictors of desistance implies refined ability to predict

persistence, which makes the most efficient allocation of prevention resources possible.

Outline of Research

Presentation of this research proceeds as follows: Chapters Two and Three review the relevant empirical and theoretical literature in order to establish the state of existing knowledge and the motivation for the current research. Chapter Two presents the relevant empirical literature on the development of aggression and provides elaborated justification for the selection of the development of aggression as the appropriate childhood risk factor to relate to later offending outcomes. Chapter Three begins with a brief presentation of the various theoretical perspectives that have been applied to investigations of desistance. Critical evaluation of each perspective is presented to justify the application or exclusion of each in shaping the proposed conceptual model. The discussion then moves to an elaboration of the theoretical models of Sampson and Laub and Thornberry, which were briefly introduced here and which provide conceptual guidance for an examination of the indirect or causal effects of early risk factors on later aspects of offending behavior. Chapter Three closes with the presentation of the conceptual model driving this research and the explicit research questions and hypotheses derived from it. Chapter Four presents detailed information on the data and sample, and outlines the specifics of the estimation techniques to be employed. Findings and results of all analyses are described in Chapter Five, and Chapter Six offers a discussion of these findings and their theoretical, empirical and

methodological implications. Chapter Six also considers the potential limitations of the findings, the new questions that are prompted by this research, and thoughts on the most productive directions for future research.

CHAPTER TWO: AGGRESSION

Introduction

The purpose of this chapter is to review the literature on aggression, and particularly that on the development of aggression during childhood as it relates to later antisocial behavior. Much of the early research on aggression focused on stability and the enduring positive association between early aggression and later problem behavior. More recently, aggression is measured as time-varying, thus reflecting a recognition that aggressive behavior during childhood reflects a pattern of development and not simply a static variable. The additional information and level of description provided by this dynamic measurement allows a more nuanced relationship to emerge. The influence of the development of aggressive development on later behavior evinces both continuity and change, suggesting the possibility that childhood aggression is important not only for its relationship with offending, but for its relationship with desistance. The clear focus on males is evident in the literature reviewed here. Where possible, gender comparisons are presented.

The Development of Aggression

Aggressive behavior up to age two is normative (Loeber and Hay, 1997; Snyder, Espiritu, Huizinga, Loeber and Petechuk, 2003), but from toddlerhood forward most

individuals learn to regulate the urge to behave aggressively (Tremblay et al, 2004). This means, in essence, that desistance from aggression in preschool is also normative. Some children, however, continue to exhibit aggressive behavior beyond preschool and into elementary school. Early research on the stability of aggressive behavior found evidence of remarkable stability (Olweus, 1979; Huesmann, Eron, Lefkowitz and Walder, 1984), but the findings from recent research employing methods designed to describe individual patterns of behavior over time temper the assertion of such stability, and show that the majority of aggressive youth eventually desist (Loeber and Hay, 1997). No gender differences are observed in infants' levels of aggression, and few differences emerge even in toddlerhood. Gender differences in levels of overt aggression do begin to emerge between ages 3 and 6, with boys showing higher rates (Loeber and Hay, 1997), and these differences in levels of aggression are exacerbated as youth enter school and during adolescence. There is consensus that boys are more physically aggressive than girls in terms of the prevalence and frequency of the behavior (Eagley and Steffen, 1986; Eley, Lichtenstein and Stevenson, 1999; Friedman, Kramer and Kreisher, 1999; Loeber and Hay, 1997; Maccoby, 1998; Maccoby and Jacklin, 1980; Maughan, Pickles, Rowe, Costello and Angold, 2000; Pepler and Craig, 1999; Tatem-Kelly, Loeber, Keenan and DeLamatre, 1997; Tiet, Wasserman, Loeber, McReynolds and Miller, 2001), and females tend to have a later onset of aggression (Loeber and Hay, 1997). This is evidence that at the very least, boys' and girls' aggression differs in absolute levels and in timing. Moreover, there is evidence that the continuity or stability of aggression among females

is less marked than for males (Broidy et al, 2003; Pepler and Craig, 1999; Schaeffer, Petras, Ialongo, Masyn, Hubbard, Poduska and Kellam, 2006). Thus the predictive power of physical aggression in childhood observed for boys is not evinced for girls (Hawkins et al, 2000; Petras et al, 2005; Petras, Chilcoat, Leaf, Ialongo and Kellam, 2004), which suggests that girls outgrow aggressive behavior more readily.

With respect to the relationship between aggression and juvenile offending, persistent physical aggression during childhood is consistently implicated as a distinct and robust predictor of serious juvenile offending for boys (Broidy et al, 2003; Farrington, 1994; Loeber, 1982; Loeber, Stouthamer-Loeber and Green, 1991; Loeber, Stouthamer-Loeber, Van Kammen and Farrington, 1991; Maughan et al, 2000; Nagin and Tremblay, 1999; Séguin, Nagin, Assaad and Tremblay, 2004). Early studies asserted the stability of aggression based on correlations of rank-ordering of the behavior at distinct points in time. Based on this early research, then, an investigation of the relationship of early aggression to later desistance would seem counterintuitive, as it was the notable persistence of behavior that emerged as the dominant theme. However, conceptual advances led to the understanding that such correlational designs are limited and do not account for the dynamic nature of behavior. In response to this conceptual recognition, longitudinal methods which are able to capture the developmental sequence, or unfolding of a behavior over time, have emerged (Muthén, 2001, 2004a; Nagin and Land, 1993; Nagin and Tremblay, 1999, 2001). These methods allow for a more nuanced understanding of behavior. Specifically, these methods illustrate the heterogeneity of

development; not all children follow the same trajectory or pathway with respect to the development of their aggressive behavior, and membership in these differing pathways may carry differing levels of risk for later problem behavior. Research employing dynamic measures of aggression has confirmed the findings of early research that aggression is one of the most significant predictors of later offending behavior and that there is considerable continuity over time. An important extension to this is that the degree of continuity an individual is likely to exhibit is conditioned largely on their membership in a given developmental pathway or trajectory.

Nagin and Tremblay (1999) investigated the relationships between trajectories of boys' externalizing behaviors and violent and nonviolent juvenile delinquency. Their sample consisted of 1,037 white males from low socioeconomic areas in Montreal whose teachers rated their aggression, opposition, and hyperactivity in kindergarten and then annually from ages 10-15. Self-reported delinquency data were obtained from the boys at ages 15, 16 and 17. Analysis of the longitudinal teacher ratings allowed Nagin and Tremblay to identify four developmental trajectories for each of the three specified externalizing behaviors: a "chronic problem" trajectory, a "high level near-desister trajectory", a "moderate level desister" trajectory, and a "no problem" trajectory. Using semi-parametric group-based modeling techniques (SPGM), Nagin and Tremblay found that membership in the distinct developmental trajectories predicted distinct types of juvenile delinquency. For example, controlling for the other trajectories, membership in the chronic opposition trajectory predicts theft only, while membership in the chronic

physical aggression trajectory led to violent and serious juvenile delinquency. Physical aggression during childhood was not found in these data to be uniquely related to nonviolent delinquency (i.e. theft). Nagin and Tremblay's findings also suggest support for Loeber's proposed developmental model (Loeber, Wung, Keenan, Giroux, Stouthamer-Loeber, Van Kammen and Maughan, 1993), which (briefly) asserts that different types of juvenile delinquency have distinct developmental pathway antecedents. Loeber's proposed developmental pathways model will be revisited in more detail in a later section. Finally, Nagin and Tremblay highlight the importance of replicating their study with a sample of females.

In one of the few studies to include females in the sample, Maughan, Pickles, Rowe, Costello and Angold (2000) use semi-parametric mixture models to compare the risk of juvenile offending for aggressive versus non-aggressive trajectory membership. Their sample is drawn from the Great Smoky Mountain Study of Youth and includes rural, predominantly white, and predominantly poor boys and girls ages 9-13. Annual assessments and parent-reported conduct problems resulted in the identification of three trajectory groups for boys and girls: stable low, stable high, and declining, for aggressive and for non-aggressive behaviors. Boys were overrepresented in the stable-high aggression trajectory, while sex differences in the non-aggressive trajectory classifications were not significant. Efforts to identify risk factors for trajectory membership resulted in the finding that a measure of inadequate parenting (specifically, poor supervision and monitoring) clearly differentiated between the stable-high and the

declining groups for both aggressive and non-aggressive classifications. An interesting finding results from comparing the aggressive and non-aggressive trajectories for overlap in classification. That is, are children likely to be classified in the same trajectory for aggressive versus non-aggressive behavior? Maughan and colleagues' analysis reveals that the classifications do not overlap to any notable degree and seem to be tapping into two distinct types of behaviors. Trajectory membership for both types of behaviors was strongly associated with risk for later police contact and arrest. The analysis of sex differences in distal offending outcomes (police contacts and arrest) is also compelling. For boys and girls, trajectory membership is a robust predictor of police contact and arrest, and when equivalent male/female trajectory groupings were compared, sex differences in offending outcomes disappeared. This finding suggests that the relationship between trajectory membership and offending outcomes does not vary by gender, and indeed that the observed differences in offending by males and females is explained, in large part, by trajectory membership. Such a finding is important and requires replication.

Brame, Nagin and Tremblay (2001) applied joint trajectory analysis to the Montreal data used by Nagin and Tremblay (1999) to investigate the existence of the oft-proposed early- and late-onset trajectories of physical aggression and violence. Much previous research directed at testing this hypothesis relies on aggregated measures of antisocial behavior which does not differentiate between physical aggression and other components of antisocial behavior. Brame and colleagues question this notion on

theoretical grounds and proceed to challenge it empirically. Their findings suggest that there is far more heterogeneity in the development of aggressive behavior over time than is recognized by the two-category typology. Brame et al. identify three trajectories of childhood aggression – low, medium and high.[2] While boys who exhibit high levels of childhood aggression are at greater risk for adolescent aggression, it is also the case that most boys on this high aggression trajectory in childhood go on to exhibit low levels of aggression in adolescence. For example, two groups are identified who exhibit moderate levels of aggression during childhood but virtually no aggression during adolescence. More interesting is the group of high level aggressors in childhood whose levels of aggression in adolescence approach zero. This group accounts for an estimated 10 percent of the population and can be classified as desisters. These three groups together comprise from 32 to 36 percent of the population, all of whom displayed some meaningful level of aggression during childhood but who did not go on to exhibit aggression during adolescence. Thus, the joint trajectory analysis offered by Brame and colleagues offers heightened sensitivity to our understanding of the continuity of behavior over time, and demonstrates that our past assertions of the absolute stability of problem behavior have been overstated. Relative stability continues to be evinced. In addition, Brame et al. find little support for the existence of a "late onset" trajectory of physical aggression. This finding confirms the initial suggestion that emerged from the aforementioned Nagin and Tremblay (1999) investigation of the same data and suggests

[2] The careful reader will note that analysis of the same data in Nagin and Tremblay (1999) yielded four trajectory groups, chronic, high level near-desister, moderate, and a no problem group. The difference in the number of trajectories identified here is the result of a different age period used to identify the trajectory groupings. In the 1999 study, trajectories were determined based on observations from age 6 to 15, while in the study under discussion here, the trajectories are derived from observations of ages 6 to 13. The chronic, non-desisting group identified in Nagin and Tremblay (1999) emerges when observations from ages 14 and 15 are included.

that perhaps those individuals identified in previous research as late onsetters where actually experiencing onset of a qualitatively different behavior.

In their analysis of 820 Canadian girls, Coté, Zoccolillo, Tremblay, Nagin and Vitaro (2001) used teacher ratings of girls' disruptive behavior from ages 6 to 12 to generate developmental trajectories, which were then used to predict conduct disorder symptoms and diagnoses when the girls were approximately 15 years old. Coté and her colleagues identified four distinct behavioral patterns: low, medium, medium-high and high. These findings call attention to the within-gender variability that exists for girls' disruptive behaviors, and contradict the findings of other studies (e.g. Silverthorn and Frick, 1999) that there is no early-starter pathway of disruptive behavior for girls. In addition, Coté and colleagues find that childhood trajectory membership ably distinguishes those girls at highest risk for conduct disorder symptoms and diagnoses during adolescence.

In an examination of gender differences in developmental sequences of offending during adolescence, Fergusson and Horwood (2002) applied SPGM to a birth cohort of 896 New Zealand males and females. Particular emphasis was devoted to an examination of Silverthorn and Frick's (1999) notion that female offending is characterized by a single developmental trajectory and late onset of offending. Fergusson and Horwood use multiple group modeling techniques to compare trajectory models for males and females. They conclude that the same model fits males and females equally well: five trajectories comprised on a chronic high and a stable low group, and three moderate trajectories

distinguished from one another by age of onset of offending. The only finding of a significant difference between males and females to emerge from their analysis was the higher likelihood of females' being assigned to lower-rate offending groups. Once trajectory membership is controlled, however, rates of offending do not vary by gender. Fergusson and Horwood also examined whether the developmental antecedents of offending differ by gender. Again, they found no significant differences. In finding evidence of the existence of an early-onset offending group of females, this research directly challenges Silverthorn and Frick's hypothesis of a single developmental pathway for female offending. However, it should be noted that 2.1 percent of females were in the chronic offender group, and only an additional 2.4 percent were in the next highest offending group – the late onset adolescent limited group. This limited representation of females in the higher level trajectories severely limits the statistical power of the study to detect gender differences in the structure and the antecedents of trajectories. Fergusson and Horwood's findings require replication with a larger sample of females.

Shaw, Gilliom, Ingoldsby and Nagin (2003) noted the significant challenges presented by elementary school-aged children with serious conduct problems, and questioned whether looking at the development of conduct problems *before* school entry could prove useful for identifying risk factors and thereby informing prevention efforts. A sample of 248 urban, low-income, ethnically diverse boys was followed from ages two to eight, and extensive data were collected on their observed problem behaviors, child characteristics, parental psychological resources, and parenting practices. Shaw and

colleagues used SPGM to identify four behavioral trajectories: a chronic high, a high-level desister, a moderate-level desister, and a stable low trajectory. The authors note the similarity of these trajectories to those frequently identified for older children, when the behavior under study is juvenile offending. As is the case for adolescents, most boys show decreasing overt antisocial behavior with age (Brame, Nagin and Tremblay, 2001; Nagin and Tremblay, 1999). In this case findings show that the decrease in overt conduct problems begins well before school age. Also consistent with the findings regarding older children, Shaw and colleagues find evidence of a small group that is not on a desisting trajectory. From a prevention standpoint, it would be ideal to isolate factors measured early in life which differentiate boys who will be in this group. An analysis of variance (ANOVA) suggested that measures of child fearlessness and maternal depression may be helpful in this regard. Multivariate logit analyses show that children with higher values on these measures - fearlessness and maternal depression - are significantly more likely to be in the chronic or high-desisting trajectories. Childhood fearlessness and maternal rejecting parenting were also able to distinguish the chronic from the high-desisting group. Shaw and colleagues' research is important for the proposed research in two ways. First, they demonstrate the importance of looking at developmental trajectories early in the life course. Second, they are among the first to identify risk factors measured so early in life that distinguish not only between the high and low rate behavior groups, but between the chronic persisters and the high desisters. This suggests a willingness to consider the heterogeneity of desistance, an idea central to

the proposed research.

Broidy and colleagues (2003) collaborated with their six distinct data sets to replicate and extend Nagin and Tremblay's (1999) work linking childhood physical aggression to offending outcomes in adolescence. SPGM was applied to cross-national data from six sites (two of which included racially diverse samples and four of which included females) to understand the relationship between the development of teacher-rated aggression in childhood and violent versus nonviolent juvenile offending. Results suggest that the continuity of behavior is particularly salient for those groups at the extreme ends of the behavioral spectrum. Specifically, chronic physical aggression in childhood is predictive of continued violence and of nonviolent offending in adolescence. When this relationship is examined for girls, however, the results are less clear. The relationship between childhood aggression and later offending does not appear to be as strong or as consistent for girls as it is for boys. It should be noted, too, that in none of the six sites was any evidence of a late-onset problem group observed. With respect to females, the chronic high girls had lower mean levels of aggression than the chronic high boys, but higher mean aggression scores than the non-chronic boys. It is interesting, then, that despite similarities in the development of aggression during childhood, females exhibit such divergent patterns of delinquent behavior versus males during adolescence.

Schaeffer, Petras, Ialongo, Poduska and Kellam (2003) applied general growth mixture modeling (GGMM) to a sample of urban boys, most of whom are African American. Their analysis of these data from the Baltimore Prevention Project (BPP)

allowed not only for the identification of developmental trajectories (based on teacher reports of aggression from 1st through 7th grades) and their links to later offending outcomes, but also for differentiation of risk factors predicting group membership. They identified four aggression trajectories (chronic high, moderate, increasing, and stable low) and found that boys in the highest risk groups - chronic high and increasing - were more likely to go on to experience juvenile and adult arrests. In an important extension to similar research to that point, Schaeffer and colleagues asked what childhood predictors may be linked with trajectory membership. They found that the "chronic high" boys had the highest prevalence of concentration problems and peer rejection, and that concentration problems are a distinguishing factor of boys with increasing aggression versus boys who exhibit stable low aggression. Replication of these antecedents of trajectory membership could prove invaluable for directing our prevention efforts in the most efficient and effective fashion.

In further analysis of the same data used by Schaeffer et al., Petras, Schaeffer, Ialongo, Hubbard, Muthén, Lambert, Poduska and Kellam (2004) recognized that while aggression trajectory membership is predictive of later antisocial outcomes, such prediction is not always perfect. An examination of "discordant" cases – those where outcomes are not what would be expected based on childhood trajectories – could therefore be informative. Note that discordance may be manifest in one of two ways. First, boys on low-risk trajectories may go on to experience antisocial outcomes. Alternatively, boys on high-risk trajectories do not exhibit antisocial behavior or

outcomes later in life. This second group may be classified as desisters. Petras et al.'s investigation, therefore, focuses in part on identifying predictors of early desistance. Among boys on the increasing aggression trajectory, reading achievement measured in first grade was predictive of discordance. For boys on the stable low trajectory, poverty and race predicted discordant outcomes. None of the predictors assessed at entry to elementary school were able to differentiate the discordant cases among the boys on the chronic high trajectory. Several middle-school factors were also significant in predicting discordance. For boys in both the chronic high and the increasing aggression trajectories, low neighborhood-level deviance was associated with lower probabilities of arrest, and for boys in the increasing trajectory only, parental monitoring was negatively associated with later arrest. Importantly, Petras and colleagues pose their question in such a way that early predictors of desistance can be identified for specific aggression trajectory groups. The identification of factors which may facilitate desistance as early as first and 6^{th} grade represents a significant advance in our prevention efforts and serves to complement our existing knowledge of adult predictors of desistance.

Subsequent analysis of the Baltimore Prevention Project data by Schaeffer, Ialongo, Masyn, Hubbard, Poduska and Kellam (2006) added Multiple Groups Analysis (MGA) to those outlined above to boys and girls in order to identify potential sex differences in the relationship between aggression trajectory membership and antisocial outcomes. A chronic-high and a stable low trajectory was identified for boys and for girls, while an increasing aggression trajectory was found for boys only and a moderate

trajectory was found for girls only. Interestingly, girls in the chronic high trajectory displayed similar initial levels and growth of aggression as boys in the analogous trajectory – a finding which contradicts that of Broidy and colleagues' (2003) of differing levels of aggression for boys and girls even across analogous trajectory groupings. Schaeffer and colleagues are the first to identify a group of girls who display identical levels of aggression as their male counterparts. However, despite the similar patterns of aggressive behavior in childhood, girls in the chronic high trajectory did not go on to experience the same rates of antisocial outcomes as boys in the chronic high trajectories. Consistent with Broidy et al., this finding suggests that the relationship between trajectory membership and offending outcomes does, in fact, vary by gender, with a less straightforward and robust relationship for girls than for boys. To return to the language and ideas of Petras et al. (2004b), perhaps it is the case that gender itself is a predictor of discordance. If this is so, a test of whether the relationship between trajectory membership and the process of desistance from juvenile offending varies by gender is warranted.

Female offending is difficult to predict. This is perhaps because of the historically low rates of female involvement in crime – low base rates (and resulting lack of variability) potentially obscure the existence of predictive or stable relationships. Much existing developmental research has cited these low rates of female involvement in delinquency as justification for the focus on boys' offending. However, Broidy and colleagues (2003) make the case that these low rates of female involvement in

delinquency are precisely the reason we should focus on girls' development. There is evidence for the existence of both boys and girls who exhibit chronic physical aggression throughout childhood. Yet despite similarities in boys' and girls' childhood aggressive trajectories, girls offend less in adolescence. In other words, a greater proportion of girls desist. If we can account for the processes that allow such divergent outcomes despite similar trajectories early in life, perhaps we can gain some insight into the process of desistance and the protective factors which may encourage it.

The research reviewed in this section provides an important foundation for the proposed research in several respects. First, the important relationship between aggression during childhood and later offending behavior is validated. Second, it establishes the importance of using appropriately measured predictors of offending, namely dynamic predictors. In the studies discussed here, the dynamic measurement of aggression and use of person-centered analysis provides greater insight into the relationship between early aggression and later offending behavior and the differential risk for offending based on trajectory membership. One observed aspect of the heterogeneity of development over time is that some individuals who would be classified as high-risk for juvenile offending according to cross-sectional measures of aggression do not actually exhibit offending behavior. It must follow, then, that dynamic measures of aggression should be employed for investigating their relationship with desistance as well.

At the broadest level, desistance is a developmental process that eventuates in the

absence of problem behavior. Implicit is the notion that there must have been some meaningful evidence of a problem behavior in the first place. In the majority of criminological research, the problem behavior of interest is offending behavior, thus overlooking the phenomenon of desistance from other problem behaviors, notably those that emerge early in the life course. With the exception of Schaeffer et al. (2003, 2006) and Petras et al. (2004b), each of these studies has identified a group of children who exhibit high to moderate levels of problem behaviors in early childhood and decreasing levels of problem behaviors into adolescence. The various manifestations of these groups across these studies and data could all be classified as desisters, and it is proposed that this group has much to offer our understanding of desistance. This process of "naturally-occurring desistance" (Maughan et al., p. 217) reminds us that, first, desistance is not limited to adolescents or adults – it can occur at any time. This sentiment is explicitly offered by Brame et al. (2001) who find that over time the modal transition for boys is to a lower-aggression trajectory. These young desisters also provide us with a unique opportunity to identify the factors associated with their desistance so that we may attempt to modify those factors for other children and facilitate a similar process of desistance for them.

CHAPTER THREE: DESISTANCE

Introduction

The purpose of this chapter is to review the literature on desistance research and to fully describe the theoretical underpinnings of the conceptual model developed for this study. I begin with a brief discussion of the definition and measurement issues unique to desistance research. This discussion provides the conceptual foundation for the next section of this chapter, which summarizes the results of empirical and theoretical explorations of desistance. Particular emphasis is given to the theoretical contributions of Sampson and Laub and of Thornberry, as both explicitly address the indirect, causal, or reciprocal effects of early characteristics and behaviors on later behavior. The conceptual model for this study, presented at the end of this chapter, draws heavily from these perspectives. Finally, I outline the questions for research and the hypotheses derived from my assessment of the extant research.

Early Desistance Research

When examined in conjunction with the other components of a criminal career (e.g. onset, frequency, continuation), the concept of desistance has received relatively scant attention (Bushway et al., 2003; Laub and Sampson, 2001; Sampson and Laub, 2003; Stouthamer-Loeber et al, 2004). There has been a change in this trend over

roughly the last ten years, and desistance is now at the fore of criminal career research. An important first step in honing our understanding of this developmental process is more clearly defining and operationalizing desistance. As it stands, there is no standard operationalization of the term (Stouthamer-Loeber et al, 2004).

In their central paper on the tenets of developmental criminology, Loeber and LeBlanc (1990) recognize that desistance is a developmental process. They define it as "the processes that lead to the cessation of crime, either entirely or in part" (p. 407). They also note that desistance is a process which can occur only for the delinquent who has engaged in recurrent criminal behavior; it is not appropriate to think of the desistance of the "occasional delinquent". Loeber and LeBlanc appear to recognize, too, that desistance is a multi-faceted process which can occur along several related dimensions and at any point in the life course. To this end, they outline four subcomponents of desistance originally proposed by LeBlanc and Frechette (1989). According to this framework, desistance may include: 1) *deceleration*, or a reduction in the frequency of offending prior to ultimate cessation 2) *de-escalation*, a move to less serious forms of offending 3) *reaching a ceiling*, which refers to an individual who stays at a given level of seriousness without escalating to more serious acts, and 4) *specialization*, a change from a varied pattern of criminal behavior to a more homogenous one, or the decline of the crime mix over time.

Despite Loeber and LeBlanc's early offering of a developmental definition and understanding of desistance, much of the subsequent research continued to define

desistance as a discrete state of nonoffending, thereby allowing for straightforward measurement (specifically, defining some cut-off point after which an individual who refrains from offending is considered a desister). For example, Loeber and his colleagues (1991) examined two years of data on boys from the Pittsburgh Youth Study and qualitatively classified the boys according to their patterns of offending. While a classification based on "patterns of offending" uses the rhetoric of a developmental measure of desistance, it is important to note that this research was based on two years of data collected on three cohorts, the oldest of which was age 14 at the completion of the follow-up period. The imposition of this exogenous and arbitrary cut-off point precludes a meaningful dynamic measure of desistance. Loeber and colleagues found that low social withdrawal, low disruptive behavior (which includes physical aggression), academic achievement, and positive motivational and attitudinal factors were associated with desistance from offending. These factors were also correlated with initiation of offending, however, and are therefore not unique to the process of desistance. The authors ultimately conclude that initiation of offending and desistance from it are simply opposite aspects of a similar process. Interestingly, their static measure of physical aggression was strongly associated with initiation, escalation, and desistance from offending.

Farrington and Hawkins (1991) analyzed data from the Cambridge Study in Delinquent Development to investigate whether each component of the criminal career has unique predictors. Their finding that early onset of offending behavior is negatively

associated with desistance from offending provides much of the empirical foundation for the developmental taxonomies such as those of Moffitt (1993) and Patterson and colleagues (Patterson and Yoerger, 1993, 2003; Patterson, DeBaryshe and Ramsey, 1989), which privilege age of onset as distinguishing between types of offenders. Farrington and Hawkins find that the most robust predictors of an early age of onset are low paternal involvement, troublesomeness, authoritarian parents, poor psychomotor skills, and interestingly, non-criminal parents. Factors associated with persistence in offending between ages 21 and 32 (and by inference, then, associated in the opposite direct with desistance) include low paternal involvement, low commitment to school, and low verbal IQ. Desistance in this study is operationalized as having a conviction through age 20 but not thereafter.

Stouthamer-Loeber, Wei, Loeber and Masten (2004) examined data on the 506 boys from the oldest cohort of the Pittsburgh Youth Study (PYS) in order to isolate those factors that are uniquely associated with desistance, as opposed to general predictors of delinquency or predictors of onset and persistence. They identify just over one third of boys ages 13-19 as chronic persistent delinquents, but of those, almost 40 percent desist from serious offending by age 25. Romantic relationship status does not differentiate between the two groups, but desisters are distinguished from their persistent offending peers by their levels of employment and schooling in early adulthood, and low physical punishment by parents during adolescence. This finding leads the authors to conclude that "… early, more distal promotive and risk factors still predict[ed] desistance even

when early serious delinquency and, later, more proximal promotive and risk effects [were] taken into account" (p. 914). It is noted that the operationalization of desistance in the study is a static one - stopping the commission of crimes. Desisters are defined as those boys who were persistent serious delinquents during adolescence but who did not engage in serious offending during early adulthood.

Uggen's (2000) paper on work as a turning point in the life course of offenders highlights the contribution of the developmental approach to our understanding of desistance. Uggen's event history analysis of data from the National Supported Work Demonstration Project confirms Sampson and Laub's (1993) finding that work is an important correlate of desistance from offending. However, Uggen's research also suggests an important caveat, that work is a causal agent for desistance only for older (ages 27 and older) offenders. This finding underscores Sampson and Laub's thesis that the effects of social bonds are age-graded. Uggen specifies his survival model according to either time-to-onset of self-reported arrest, or time to the first spell of illegal earnings during a three year follow up period.

These studies have been important for identifying factors which may be related to desistance and have provided a good foundation from which to continue our research. However, the eventual recognition that desistance is not a discrete state (as it is measured in the aforementioned studies) but rather a developmental process casts serious doubt on the utility of these studies to accurately identify desisters. If the desisters themselves are not accurately identified, then the factors associated with their desistance must also be

viewed with caution.

Dynamic Measures of Desistance

Bushway, Thornberry and Krohn (2003) provide a convincing account of the inadequacies of static measures of desistance, chief among them the arbitrary nature of the cutoff points between offending and post-offending periods, the fact that the heterogeneity of offending careers demands some heterogeneity in the process of desistance not accounted for by static measures, and the potential for identifying false desisters in the absence of a sufficiently long follow-up period. Bushway and colleagues propose, then, that desistance be defined as "the process of reduction in the rate of offending from a nonzero level to a stable rate empirically indistinguishable from zero" (Bushway, Piquero, Broidy, Cauffman and Mazerolle, 2001:500; Bushway et al, 2003:133). This definition distinguishes the developmental process of desistance from the discrete state of termination, the point at which one ceases to offend (Laub and Sampson, 2003). It allows for the possibility of multiple pathways to desistance. Bushway and colleagues then apply different measures of desistance to data from the Rochester Youth Development Study to demonstrate the differences in results. When the static approach is employed (they identify anyone who offended before the age of 18 but not thereafter as a desister), 27.6 percent of the sample meet the criterion for desisting. The dynamic measure of desistance requires estimation of a semi-parametric group based model (SPGM), which is advocated as an appropriate methodology for capturing

heterogeneity in developmental processes. This method identifies seven patterns of offending behavior, only one of which comprises desisters. This group represents 8.4 percent of the entire sample. Bushway and his colleagues propose that the notably larger group of desisters identified by the static approach includes individuals who did not experience meaningful change during the course of study. These individuals exhibited low levels of criminal involvement during the pre-cutoff period and, not surprisingly, did not offend after the cutoff period. Closer consideration of this group suggests that they actually exhibit stability in their behavior over time, that their rates of offending were never meaningfully different from zero. Indeed, Sampson and Laub (2003) caution that our examinations of desistance should be directed toward those offenders for whom desistance represents meaningful change, as desistance from low-level offending is normative (see also Laub and Sampson, 2003). In this instructive comparison of static versus dynamic measurement of desistance, Bushway and his colleagues make clear that a static approach to desistance is not likely to be enlightening. In addition, the dynamic approach they advocate provides richer information as to the timing and slope of the process of desistance.

To a great extent, the operationalization of desistance determines which modeling strategies can be appropriately applied. This recognition prompted Brame, Bushway and Paternoster (2003) to question the consequences of parametric assumptions imposed by modeling strategies, particularly with respect to identifying desisters. Their illustration, based on analysis of the 1958 cohort of the Philadelphia Cohort Study, provides further

support for Bushway and colleagues' earlier conclusion and caution that desistance research is particularly sensitive to differences in operationalization and measurement. Results must be critically examined and assessed in light of measurement of the construct and the assumptions of the modeling strategy.

There is general agreement that there are multiple pathways to desistance (Sampson and Laub, 2003), but not as to the causes and correlates of it. Indeed, very little is known about the causal processes of desistance (Piquero, Farrington and Blumstein, 2003). Unfortunately, much of the existing research on the causes and correlates of desistance involves the (mis)application of static measures to capture a dynamic process. The research reviewed above suggests that this body of research has limited utility, at best, for enlightening the process. Fortunately, in response to the theoretical recognition that desistance is a developmental process, and with the introduction of analytic techniques capable of treating it as such, new studies emerged which employed dynamic measurement of desistance.

In response to Sampson and Laub's important findings on the influence of adult social bonds on long-term change (see Sampson and Laub, 1993), Horney, Osgood and Marshall (1995) extend the inquiry to an examination of the influence of "local life circumstances" (p. 655) on the intermittency of offending patterns, or short-term change. Local life circumstances are those situations or conditions that are subject to frequent fluctuation and shift, such as corrections experiences, intermittent drug use, or temporary cohabitation. Horney and her colleagues apply hierarchical linear models to month-to-

month data on 658 convicted male offenders. Their finding that local life circumstances are associated with meaningful short-term changes in adult male offending behavior, independent of stable individual differences in offending propensity, confirms and extends the earlier findings of Sampson and Laub. Their findings also provide an important complement to Sampson and Laub's empirical work by showing that the effects of local life circumstances are, at times, themselves quite transient and short-lived.

Laub, Nagin and Sampson (1998) hypothesize that desistance is a consequence of investment in social relationships. The formation of social bonds based on these relationships is a gradual process, and so desistance must be a gradual process as well. To test their hypothesis, Laub and his co-authors apply trajectory analysis to describe the dynamic patterns of desistance in the Glueck data. They find support for their hypothesis that quality marital bonds facilitate the process of desistance, and by implication, childhood characteristics are insufficient for predicting the full course of offending.

Each of these studies was perhaps motivated by, and certainly supports, the findings of the seminal work by Laub and Sampson (2003; Sampson and Laub, 1993). This body of work was introduced in 1990 and has stimulated consistent attention and discussion ever since. The recent publication of *Shared Beginnings, Divergent Lives* (2003) provides a comprehensive summary of the development of their Age Graded Theory of Informal Social Control (discussed in more detail in a later section), the significant empirical support for their theory, and importantly for the present discussion, their recent findings on patterns of desistance among the Glueck men, five hundred male

delinquents born in Boston between 1924 and 1932. In the longest longitudinal study in criminology, Laub and Sampson followed-up a sub-sample of these men to age seventy. Most of these men would have been classified as chronic, persistent offenders during their adolescence, and for some this was the case well into their adult lives. Laub and Sampson find that marriage and employment, and the informal social control generated by a positive experience with either, are critical in explaining desistance from crime. When coupled with human agency or a personal individual choice to stop offending, marriage and work provide the social context and situational structure that eventually results in desistance.

Assessing the Status of Desistance Research

The foregoing discussion allows for some conclusions regarding the process of desistance, and suggests some unanswered questions which warrant further consideration. Conceptually speaking, it is by now clear that desistance research must employ a dynamic, developmentally-oriented definition and operationalization. Empirically speaking, thorough and rigorous research has identified several proximal correlates and predictors of desistance, with sufficient replication that their place in any discussion of desistance is irrefutable. Chief among these are marriage and work, as identified by the research of Sampson and Laub.

The empirically established predictors of desistance are all factors which emerge in adulthood. Each of the studies that employed a dynamic measure of desistance found

that proximal influences explain changes in adult offending patterns, net of childhood characteristics. However, these childhood characteristics are measured and modeled as static predictors, which do not fully capture the early developmental processes that shape later ones. Thus, the question of the influence of childhood development on desistance remains open. In addition, with the ultimate goal of fostering desistance as early in the life course as possible, the identification of factors which predict desistance *before* adulthood would be ideal. Finally, the existing findings from desistance research apply only to males. More research is needed to examine whether the predictors and processes of desistance are different for females. This study addresses these gaps in the existing literature with an examination of the relationship between the developmental course of aggressive behavior in childhood and continuity and change in later offending. The extent to which gender contextualizes this relationship is also explored. Before the conceptual model and research hypotheses are presented, the theoretical landscape of desistance research is considered.

Theoretical Frameworks for Understanding Desistance

While most criminological theories can be interpreted with respect to their implications for desistance, Sampson and Laub (1993) provide the only causal theory explicitly articulated to explain desistance. Generally, however, we must rely upon broader theoretical frameworks to provide the basis for inferences about the process of desistance. Laub and Sampson (2001) summarize five such frameworks:

age/maturation, rational choice, social learning, developmental, and life-course perspectives.

Perhaps the simplest theoretical account for desistance is the proposition that it is a function of maturation and aging. This theory was originally advanced by the Gluecks (1950), who felt that the natural physical and mental changes which accompany maturation account for the cessation of offending behavior. Desistance is therefore the inevitable result of time passing, and variability in the timing and rate of desistance is explained by the delayed maturation experienced by some persistent offenders. Whereas the Gluecks viewed maturation as linked, but not synonymous, with age (Laub and Sampson, 2001), Gottfredson and Hirschi (1990) posit a direct relationship between age and crime, such that crime declines with age. While the distribution of criminality in the population remains relatively stable, crime declines with age for everyone; hence desistance.

Rational Choice theory asserts that the decision to engage in crime is the result of an evaluation of the anticipated costs and benefits associated with crime (Cornish and Clarke, 1986). This cost/benefit analysis is an iterative process, and the factors under consideration may change over time. This rational decision making process applies to every component of the criminal career. A rational choice explanation for desistance, then, asserts that the cessation of offending is the result of increasing fear of punishment (Cusson and Pinsonneault, 1986; Laub and Sampson, 2001) and the perception of decreasing rewards associated with crime (Laub and Sampson, 2001; Shover and

Thompson, 1992).

As is the case for Rational Choice explanations for desistance, proponents of a social learning approach argue that the causal mechanisms proposed by the theory apply equally well to every component of the criminal career, be it onset, continuation, or desistance. Thus, a distinct theory of desistance is not required; the original tenets of social learning theory are able to account for desistance. Akers (1985) begins with differential association theory, which argues that an individual will learn criminal behavior through exposure to delinquent others and subsequent adoption of definitions favorable to crime. Akers expands upon the theory by describing the process of how an individual incorporates "definitions favorable to violations of law" (p. 39). Relevant to a discussion of desistance is Akers' notion that differential reinforcement of a behavior determines whether that behavior will continue. Over time and as offenders age, they are less likely to be exposed to delinquent peers and therefore do not receive the same positive reinforcement of their criminal behavior.

The three theoretical frameworks reviewed thus far have much to offer our understanding of the process of desistance. Each attempts, in its own way, to account for the behavioral change evinced in desistance, and as such each must include some consideration of change over time. Gottfredson and Hirschi excepted, each argues that it is not time (or age) in and of itself that leads to desistance, but some social or psychological change process that unfolds over time. However, for the developmental and life course perspectives, the relationship between age and behavior is a fundamental

component of even the most basic expression of the perspective, rather than a possible extension of it.

A developmental approach to explaining desistance refers to incorporating consideration of early influences on later behavior, both theoretically and methodologically. A number of developmental theories have been put forth which may guide our thinking about desistance. For example, Moffitt's Developmental Taxonomy (1993) identifies two distinct groups of offenders: the adolescence-limited (AL) and the life-course persistent (LCP) offender. The adolescence-limited offender is more common. For these individuals, delinquency is the result of short-term social processes which lead to psychological discomfort (Moffitt, forthcoming) and as such, offending is limited to the adolescent years. This psychological discomfort stems from the "maturity gap" (p. 3), which Moffitt defines as the discordance between an adolescent youths' emerging biological maturity and their desire for, but lack of access to, adult privileges and responsibilities. The ALs' offending represents their attempt to close that gap – offending behavior is a form of social mimicry of the LCP and is thought to establish autonomy from parents and to cement affiliations with peers. As the maturity gap closes, the AL desists. The AL offender has experienced normal pre-offending development, and once the short-term social inducements to offending are removed, a conventional lifestyle is resumed. Varying rates of desistance across ALs are explained by "snares" such as addiction, criminal conviction, or retarded educational attainment resulting from involvement in delinquency.

Life-course persistent offenders account for about 10% of the population but about 50% of offending (Caspi and Moffitt, 1995). LCPs start offending at earlier ages (indeed, age of onset serves to distinguish between the two types of offenders) and offend at greater frequency, severity, and duration. It is for the LCP that early childhood risk factors are of particular importance. Neuropsychological vulnerabilities, frequently manifest as hyperactivity or a difficult temperament, place a child at greater initial risk for problem behavior. These cognitive deficits then interact with a difficult socializing environment, which may include inadequate parenting, poor bonding to family, and poverty (Moffitt, forthcoming). This interaction is likely to eventuate in a persistent offender. Moffitt acknowledges that most LCPs eventually desist, but points to their continued involvement in other antisocial behaviors and increased negative life outcomes as evidence for the persistent nature of their antisocial personality structure.

Patterson and Yoerger's (1993, 1999, 2002) developmental model was motivated by their observation that there is heterogeneity among juvenile delinquents with respect to their levels and course of offending, and the outcomes they experience as adults. Their analysis of the Oregon Youth Study (OYS) data leads them to propose that two theoretical models of delinquency are required, one for the early starter and one for the late starter. The antisocial behavior of the early starter begins with overt problem behavior in toddlerhood and progresses to delinquency by age fourteen. The genesis of the overt problem behavior is ineffective socialization caused by coercive parenting, which in turn produces oppositional and disruptive behavior. This behavior leads to

rejection by conventional peers and facilitates deviant peer associations. Thus the problem behavior of the toddler triggers a state dependent process whereby antisocial behavior is canalized, and opportunities for effective socialization diminish over time. In contrast, the late starter in Patterson and Yoerger's theory has been effectively socialized. Their delinquency is temporary, resulting from the increased association with deviant peers that characterizes the conventional adolescent experience. Thus, the late starter is never truly antisocial. The implications for desistance in Patterson and Yoerger's theory are similar to those for Moffitt's taxonomy. Desistance is expected and normative for the late-starter, for whom delinquency is influenced only by proximal and short-lived social factors, namely a deviant peer group. Desistance for the early starter is more problematic, as their offending behavior is a reflection of an underlying antisocial personality structure interacting with disrupted parenting practices.

A final example of a developmental theory which may inform our thinking about desistance comes from Loeber and colleagues (Tatem-Kelley, Loeber et al, 1997), who propose the existence of three distinct developmental pathways of early problem behavior - covert, overt, and authority conflict. Each of these three pathways has different outcomes in terms of the types of offending observed in adolescence. The covert pathway begins with minor transgressions such as shoplifting and lying and may proceed to more serious forms of covert antisocial behavior such as property damage, burglary and serious theft. The authority conflict behavior begins with stubborn behavior and may progress to defiance and avoiding authority by running away, truancy, and curfew

violations. Finally, the overt pathway begins with minor aggression (bullying, for example) and may progress to physical fighting and ultimately to serious violence. Individuals can develop along more than one pathway at a time. Loeber's framework recognizes the sequential nature of problem behavior and the progression from less to more serious forms of each types of behavior. Of particular relevance to the present research is the Overt Pathway, which begins with minor aggression. Loeber's model presents each pathway as though it represents a homogenous group[3], which is not likely the case and will be examined in detail with this study. Additionally, empirical support for Loeber's pathway model comes from data comprised entirely of males (for examples, see Loeber, Farrington, Stouthamer-Loeber and Van Kammen, 1998; Loeber et al., 1999). The relevance of his theoretical propositions for the development of problem behavior in girls remains an open question.

Sampson and Laub's Age-Graded Theory of Informal Social Control (Laub and Sampson, 1993, 2003; Sampson and Laub, 1993) embodies the life-course account of desistance. The full model is discussed in detail below, so the theory is not summarized here. Of relevance for this section is Sampson and Laub's assertion that because the life-course perspective emphasizes explaining within-individual changes in behavior over time, it is best suited to explain desistance.

Laub and Sampson draw theoretical distinctions between the life-course and developmental perspectives. The developmental perspective, in their assessment, does not make sufficient allowances for the possibility of change, particularly that which

[3] To be fair, Loeber proposes a heuristic model to explain the progression from predelinquent problem behavior to delinquency and offending. His language may be necessarily stylized in order to efficiently convey the basic propositions of the theory.

might emerge after childhood. Thus, the systematic aspects of development are overstated, to such a great extent that development actually resembles "the execution of a program written at an earlier point in time" (2003:33). I argue, however, that their characterization of the developmental perspective is similarly overstated, or perhaps is relevant for applications of the developmental perspective in other fields of study, such as evolutionary genetics. It is true that many developmental theories of criminogenesis identify a small group of offenders who seem largely impervious to change, and the stability of their behavior is attributed to childhood characteristics (to wit, the developmental theories of Moffitt and Patterson discussed above). The identification of childhood factors that account for longitudinal stability, however, does not demand the disavowal of the influence of later-life influence and of the possibility for change.

It is possible that Laub and Sampson's criticisms of the developmental perspective are more appropriately directed to a few specific theories that clearly derive from a developmental approach, rather than to the perspective itself. Moffitt's Developmental Taxonomy, for example, is frequently presented as the apotheosis of developmental criminology, and the taxonomic component of her theory in particular has been the subject of intense focus. If a consequence of this focus is that Moffitt's specific articulation of a developmental theory has supplanted the original tenets of the perspective, then a stark distinction between life-course and developmental perspectives is warranted. However, an appreciation of the developmental perspective in its original form (see Loeber and LeBlanc, 1990) finds more common ground than points of

disagreement with the life-course perspective. Sampson and Laub seemed to share this view in 1993 when they wrote *Crime in the Making*. They originally characterized their theory as a "sociogenic developmental theory" (p. 246), consistent with Loeber and LeBlanc's definition of developmental criminology as "strategies that examine within-individual changes in offending over time" (1990: 433 as cited in Sampson and Laub, 1993). The emphasis on understanding longitudinal patterns of individual behavior within social and structural contexts is common to the life-course and developmental perspectives (Elder, 1975; Loeber and LeBlanc, 1990), as is the recognition that consideration of early childhood development is critical for achieving this objective. It is this interpretation of the developmental and life-course perspectives, and the interpretation originally embraced by Sampson and Laub, that informs this study. In fact, the conceptual model presented at the end of this chapter draws heavily from Sampson and Laub's theory, and from Thornberry's Interactional Theory of Delinquency (1987).

Sampson and Laub's Age Graded Theory of Informal Social Control

Sampson and Laub (1993; Laub and Sampson, 2003) offer an Age-Graded Theory of Informal Social Control to account for the longitudinal sequence of offending over the life course. The central premise of their theory is that bonds to conventional institutions such as work and marriage exert social control over an individual, which then restrains the individual from engaging in crime. When these bonds are nonexistent or weak, criminal behavior is more likely. Any persistent absence of social control, then, accounts

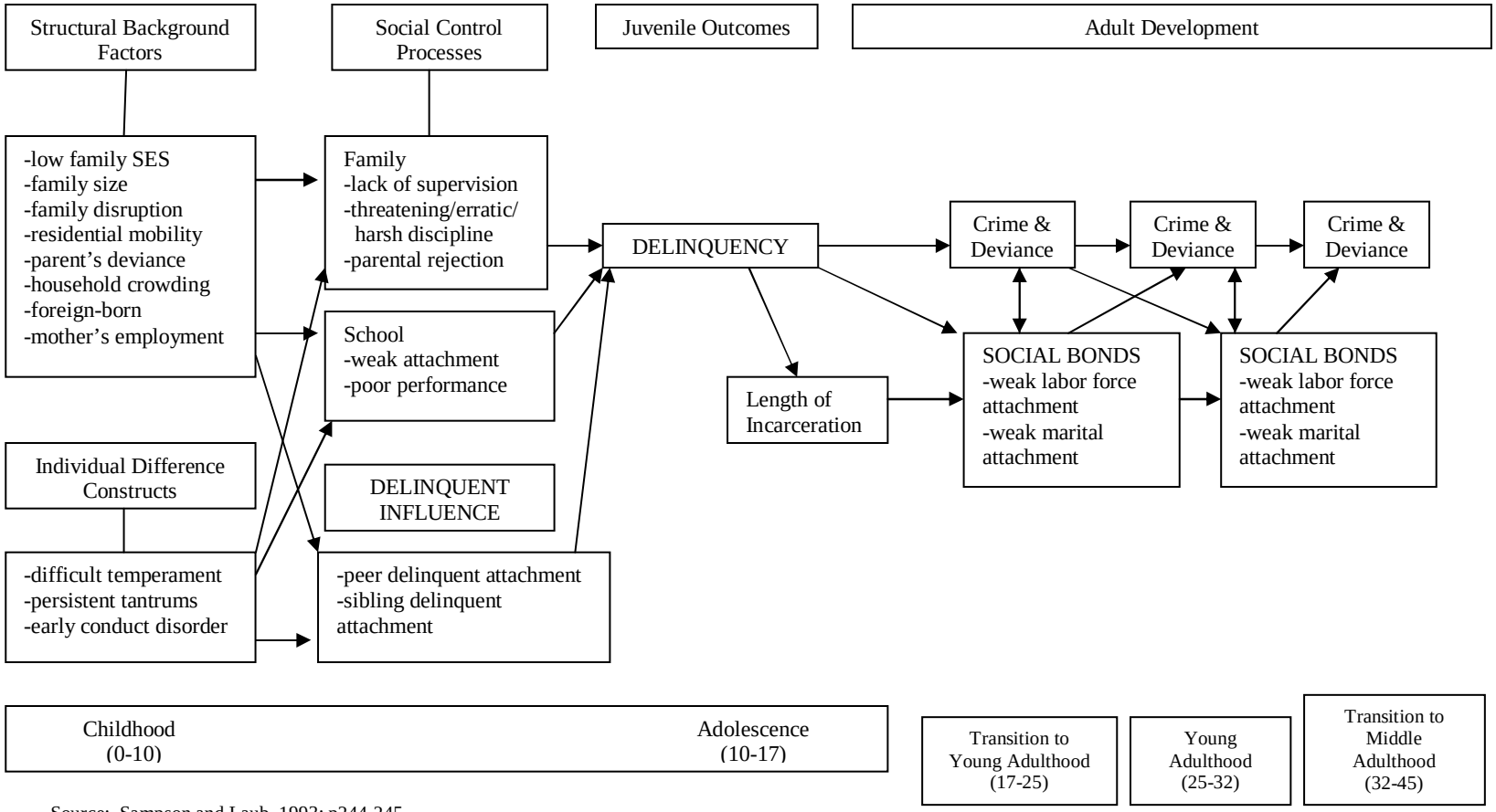
for persistence in offending. Conversely, the presence or emergence of social control created by social bonds explains desistance from crime. Sampson and Laub include consideration of the influence of structural factors (for example, socioeconomic status, family size, parental employment) and individual differences (for example, temperament and conduct disorder during childhood) on the processes of social control. Ultimately, however, structural background factors are indirect distal influences, and are mediated by informal social control. Figure 3.1 provides a graphical representation of their theoretical model.

Sampson and Laub emphasize the importance of the reciprocal nature of causal influences of offending. This is particularly evident in the Adult Development phase of their dynamic conceptual model, which illustrates the iterative relationship between criminal behavior and weak social bonds. Weak social bonds facilitate criminal involvement, which in turn further weakens social bonds, thereby increasing the likelihood of future offending, and so forth.

Sampson and Laub are widely recognized for their contribution to our understanding of continuity and change in offending during adulthood. Much of their work has focused on explaining desistance from crime during adulthood. Fundamental to their theory, however, is that it is derived from a life course paradigm, and has the ability to explain crime across said life course. Delinquency in childhood and adolescence is explained by family and school processes of informal social control. Adolescent delinquency is an important variable in their model, as it predicts weak adult social

bonds. However, adolescent delinquency is not sufficient for predicting adult offending behavior, as evidenced by the notable degree of discontinuity observed in criminological research across time, place, and sample. According to their theory, the presence or absence of social bonds in adulthood is a more powerful and salient influence on concurrent and later behavior. In their final empirical models, Sampson and Laub find that once background factors and past behavior are controlled, social bonds do in fact account for the observed variation in the course of adult offending. This finding establishes the importance a focus on adulthood for a comprehensive understanding of desistance across the entire life course. However, it does not obviate consideration of the effects – whether direct, indirect, or mediated – of early childhood development on shaping (but not determining) later desistance.

Figure 3.1 Sampson and Laub's Theoretical Model



Source: Sampson and Laub, 1993: p244-245

Giordano, Cernkovich and Rudolph (2002) question the extent to which Sampson and Laub's theoretical model generalizes to women, minorities, and contemporary populations. Their analysis of a sample of serious female delinquents[4] finds that neither job stability nor marital status are related to female desistance, and thus challenges the applicability of Sampson and Laub's theory for females. Giordano and colleagues then propose an alternative "provisional" theoretical model intended to address this limitation. Informed by their impressions from unstructured life history interviews, Giordano and colleagues offer their theory of "cognitive transformation" (p. 991), which they align with the symbolic interaction tradition. Briefly summarized, behavioral change is necessarily preceded by a cognitive shift – a change in one's fundamental identity and assessment of the desirability of criminal behavior. Pursuant to this cognitive shift, the offender exercises increased agency in shaping their environment so that it is consistent with (and conducive to) their newly emerging identity. Giordano and her colleagues assert that this "agentic" take on desistance avoids the restrictive assumptions imposed by theories of desistance grounded in classical control theory, such as Sampson and Laub's. The vulnerability in their argument is that the assumptions to which they refer – that an individual's propensity to offend is a constant and variation in behavior results entirely from the degree of control exerted over an individual – are certainly implicit in classical control theory, but are not retained in Sampson and Laub's theory. In fact, the notion of human agency is central to Sampson and Laub's articulation of control theory. Thus, if Giordano, Cernkovich and Rudolph's theory of desistance is based on increased social

[4] The sample also includes 101 "similarly situated males" (p. 990). However, the focus of Giordano and colleagues' research, and the relevant content for the present discussion, is the sample of 109 females.

connectedness stemming from an agentic decision to align oneself with prosocial others, it is not the "theoretical counterpoint" (Giordano, Cernkovich and Holland, 2003: 295) to Sampson and Laub's theory, but rather a symbolic interaction translation of it. Theoretical redundancy notwithstanding, Giordano and co-authors' empirical findings raise the compelling possibility that the causal processes that result in desistance for women differ from those for men. In the absence of other empirical evidence specific to women, this possibility demands further consideration.

Thornberry's Interactional Theory of Delinquency

Thornberry identifies several critical limitations of existing theories of criminogenesis, and proposes his Interactional Theory of Delinquency (1987; Thornberry, Lizotte, Krohn, Farnworth and Jang, 1994) to address them. He observes that many theories assume recursive causal relationships between delinquency and other variables, when in fact the occurrence of delinquency itself is likely to have a state dependent impact on subsequent behavior. Delinquency therefore must be conceptualized as both a cause and an effect of social processes. Thornberry also offers the related criticism that few theories adequately address the developmental progression of behavior over time. Many theories of delinquency focus on adolescence because offending behavior is most likely to occur during this developmental period. When the focus on adolescence is exclusive, however, the causal influence of the preceding developmental patterns is ignored. Finally, many theories ignore the influence of social

structures and context on the dynamic process of behavioral development. To address these limitations, Thornberry reformulates the causal hypotheses of social control theory, social learning theory, and integrated models into an explicitly developmental framework.

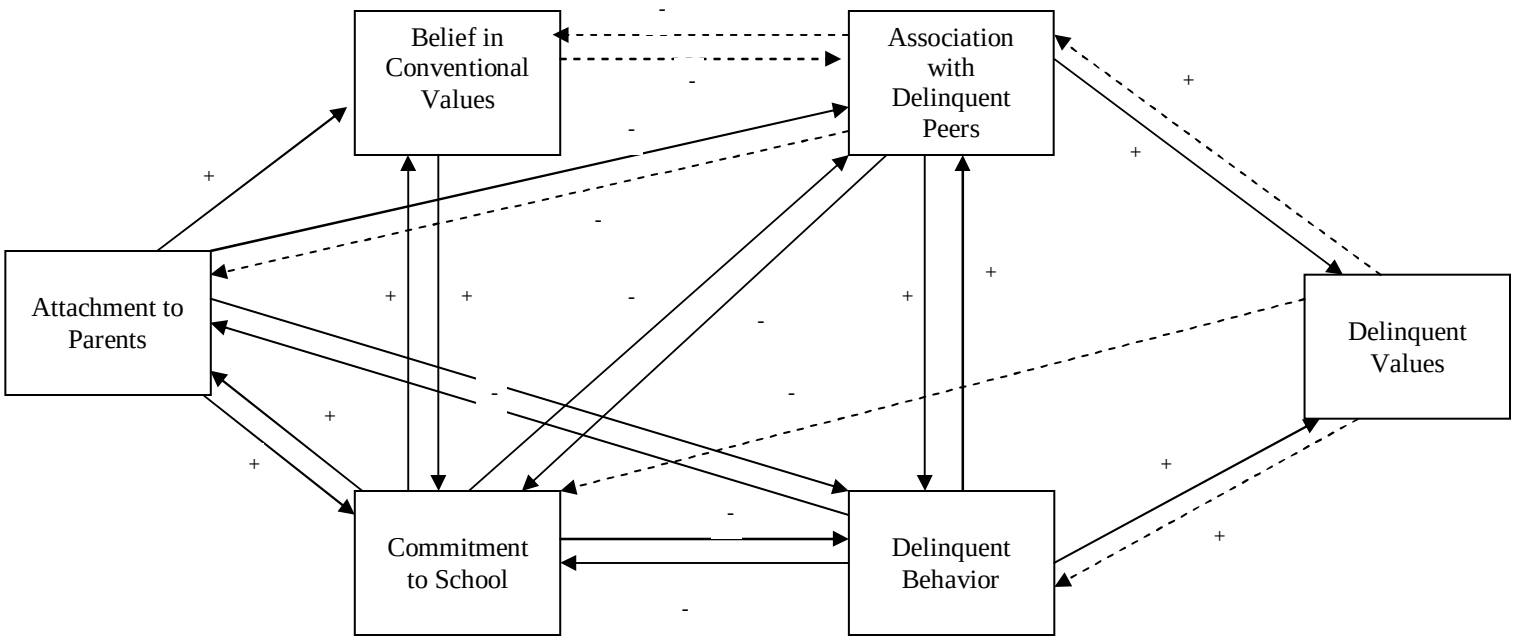
The guiding principle of Thornberry's Interactional Theory of Delinquency (ITD) is that all behavior, including delinquent behavior, occurs in social interaction. By implication, models intended to explain behavior must allow for interactional and reciprocal relationships among variables. The variables of interest with respect to delinquency are attachment to parents, commitment to school, belief in conventional values, association with delinquent peers, delinquent values and delinquent behavior itself. None of these are static characteristics; they likely vary over time, and each interacts with the other throughout the developmental process.

Social control theory (Hirschi, 1969) provides the conceptual starting point for ITD. Thornberry asserts that the causal process of delinquency begins with weakened social controls. The primary social controls at work derive from attachment to parents, commitment to school, and belief in conventional values. Thornberry moves beyond classical social control theory with his notion that the attenuation of control does not necessarily lead directly to delinquency; it simply allows for greater freedom of behavior. Delinquent behavior is one potential outcome in a greater array of behavior. In order for weakened controls to eventuate in delinquency, a weakly controlled individual must be exposed to a social learning process that models and reinforces delinquency. Social

structure and environmental context are important for shaping the extent to which delinquency behavior is learned and reinforced, which in turn influences the extent to which delinquent behavior is perpetuated. In addition, the weakened bonds that are the fundamental cause of delinquency are reciprocally related to it. That is, the weakening of the bond provides the initial cause of delinquency, but delinquency becomes its own indirect cause over time because it further weakens the already tenuous bonds to family, school, and conventional beliefs.

So explicit is the developmental perspective in Interactional Theory that three separate models are required to illustrate the theory. Thornberry provides a model for early adolescence (ages 11-13), one for middle adolescence, and one for later adolescence. Each causal model outlines the reciprocal relationships among the six concepts of interest: attachment to parents, commitment to school, belief in conventional values, association with delinquent peers, delinquent values and delinquent behavior. The nonrecursive structure of the model allows Thornberry to divest himself of the temporal ordering quandary typically attendant to discussions of the causal relationships among delinquent peers, beliefs, and behavior. He reasons that individuals frequently adopt some version of the attitudes and beliefs of their associates, as suggested by a strict social learning model, but simultaneously seek out like minded and "like behaved" peers, as is the case within a strict selection model. The relationship is a bidirectional one, and is modeled as such. Figure 2.1 details the early adolescence model and the reciprocal relationships among the bonding, learning, and structural variables.

Figure 3.2 Thornberry's Interactional Theory Model (at Early Adolescence)



Solid lines represent stronger effects; dashed lines represent weaker effects.
Source: Thornberry, 1987: p871.

The common contribution of Thornberry's and Sampson and Laub's theories is the recognition that current behavior is best understood in the context of the developmental pathways that precede it. A synthesis of the two perspectives yields a clear articulation of the proposed linkage between early childhood aggression and desistance from adult offending: Desistance from offending in adulthood is explained by informal social control, which is explained in large part by prior delinquency. Delinquency cannot be explained without due consideration of the phases of development that preceded it, so we must look to childhood development. During childhood, the dynamic interaction of social structure with parental, school, and peer influences determines the extent of a child's bonds to convention and to prosocial others. These bonds, or rather the social control they exert, are the fundamental explanation for variation in offending behavior.

The Conceptual Model

The conceptual model depicted in Figure 3.3 outlines the hypothesized relationship between developmental patterns of aggression during elementary school and various aspects of juvenile offending and adult offending.

Inadequate socialization in the home places a child at risk for encountering difficulties upon entering the school environment. Difficulty with school attainment and rejection by peers not only continues the failed socialization process, but also likely facilitates association with rejected or non-socialized others.

Repeated measures of aggression from first through third grade provide the information required to estimate latent classes[5], which differentiate the distinct behavioral patterns that emerge. These patterns are then used as an independent variable that influences the onset, seriousness, and duration of offending. The box on the left-hand side of the figure identifies several theoretically derived covariates thought to influence levels and patterns of aggressive behavior.

Model Covariates

Race is one of the most robust – if least understood – correlates of offending behavior. African-American youth are disproportionately represented in the juvenile justice system (Poe-Yamagata and Jones, 2000; Snyder and Sickmund, 1999). Research also suggests that race is an important correlate of predelinquent problem behavior. For example, evidence indicates that African-Americans are rated higher on externalizing behavior (Zimmerman, Khoury, Vega and Gil, 1995). Race is therefore an important consideration for any investigation of problem behavior. In the present conceptual model, I hypothesize that minority status will be positively associated with membership in the trajectories that describe more problematic behavior.

Eligibility for free lunch provides a proxy measure of socioeconomic status (SES). Sampson and Laub's and Thornberry's theories include consideration of the importance of social and structural contexts for shaping behavior. Disadvantaged economic status is an important component of this context, which has been related to a host of negative life outcomes, including criminal involvement (Dodge, Pettit and Bates, 1994; Greenberg,

[5] Variations of the terms latent classes, trajectory groups, and class membership are used interchangeably in discussing this model and the empirical findings reported in subsequent chapters. Each term is simply an efficient way to talk about the various patterns of aggressive behavior that emerge in the data.

Lengua, Coie and Pinderhughes , 1999; Leventhal and Brooks-Gunn, 2000). Nagin and Tremblay's (1999) finding that low socioeconomic status (SES) discriminates trajectories of antisocial behavior among school-aged children also supports that SES is an important consideration in studies of antisocial behavior. Previous research has shown that free lunch status correlates highly with other traditional measures of socioeconomic status and family poverty (Ensminger, Forrest, Riley, Kang, Green, Starfield and Ryan, 2000). I expect that students who are eligible to receive free lunch will be overrepresented in the high and chronic trajectories of aggressive behavior.

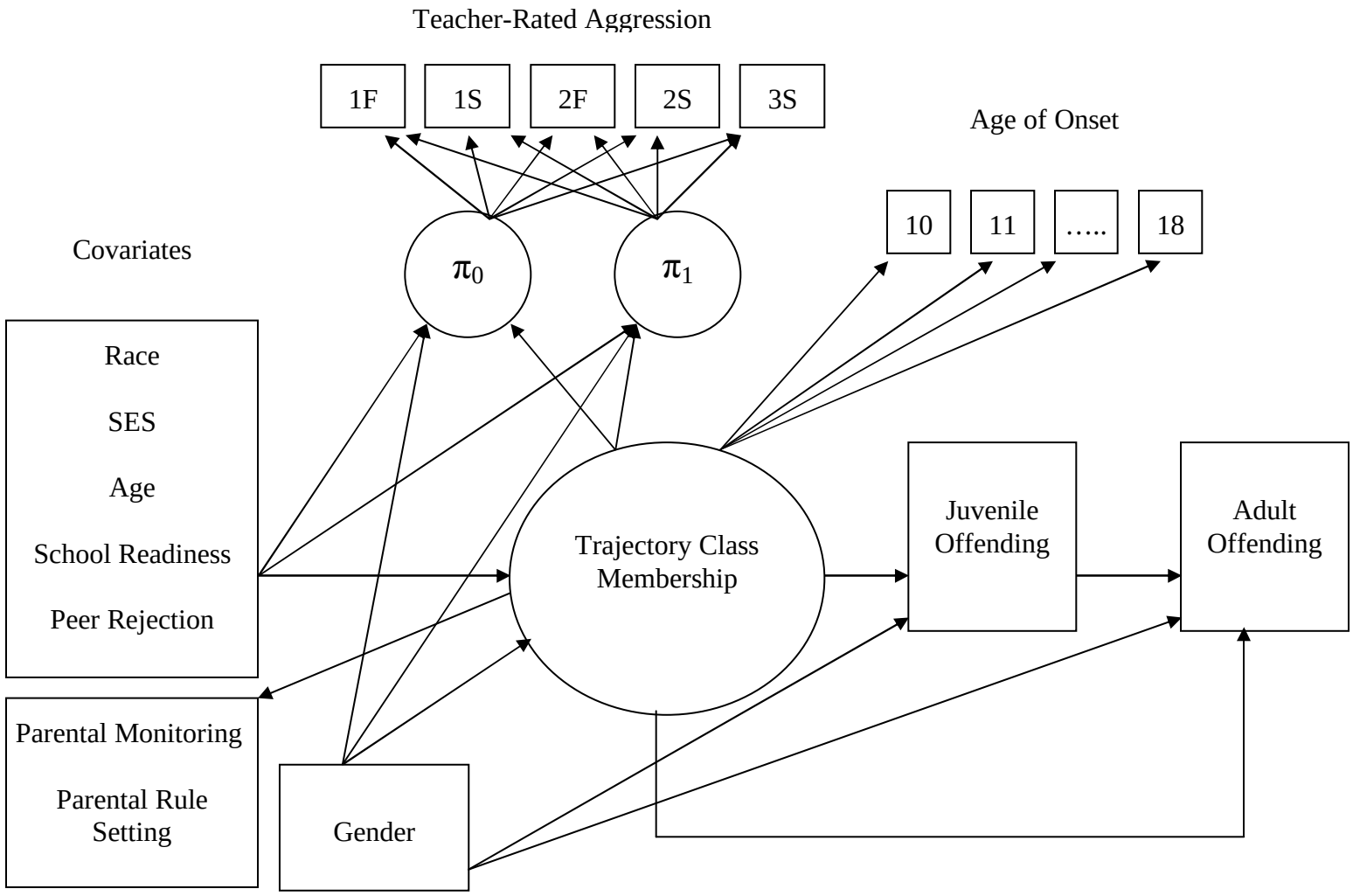
Age at first grade entry is included to account for the consistent empirical observation that for most children, overt problem behavior decreases as a function of age (Broidy et al, 2003; Loeber and Hay, 1997; Nagin and Tremblay, 1999; Pepler and Craig, 1999). Children who are slightly older at the start of first grade may experience a protective effect of their age, and therefore will more likely exhibit behavior consistent with a low-level pattern of aggression.

Academic attainment and attachment to school are essential components of a child's early experiences with social bonds, and play key roles in the theories informing this conceptual model. *School Readiness* is therefore included as a covariate to tap into this dimension of early development. Cognitive abilities and intellectual functioning strongly predict offending and other behavior problems (Farrington, 2003; Moffitt, 1993; Wilson and Herrnstein, 1985; Yoshikawa, 1995). Several prominent developmental theories of criminogenesis assert that a child's intellectual and cognitive functioning mediates the relationship between family process risk factors and problem behavior outcomes (for example, Moffitt and Caspi, 2001; Moffitt, Caspi, Dickson, Silva and Stanton, 1996). This

proposed relationship has been borne out in empirical work, where findings indicate that intellectual functioning and school attainment predict to trajectory class assignment (Petras et al, 2004b; Schaeffer et al, 2003). School readiness is expected to serve as a protective factor, with children who are more prepared for school exhibiting lower levels of aggression.

Peer Rejection is positively correlated with aggressive behavior (Hymel, Rubin, Rowden and LeMare, 1990; Rubin, 1982; Rubin and Clark, 1983; Rubin, Daniels-Beirness and Hayvren, 1982), and with later delinquency (Patterson, Capaldi and Bank, 1991; West and Farrington, 1977). Several theoretical positions point to peer rejection as a facilitator of association with delinquent peers, which is itself among the most robust predictors of juvenile delinquency (Gifford-Smith, Dodge, Dishion and McCord, 2005). Coie, Lochman, Terry, and Hyman (1992) noted the high correlation of peer rejection and childhood aggression and the relationship each seems to have with adolescent maladaptive behavior, including delinquency. To address the question of the unique contribution of each, they analyzed three years of data on a large sample of Black, primarily poor, boys and girls from Durham city schools. Their results show that both aggression and peer rejection are important for their unique relationships with adolescent offending behavior. Peer rejection is also highly predictive of early school withdrawal (Coie et al, 1992). This relationship highlights the importance of Sampson and Laub's notion of cumulative continuity of disadvantage, and Thornberry's emphasis on the relevance of prior states and behaviors for understanding contemporaneous behavior. Based on the empirical evidence and the theoretical accounts of it, I expect that peer rejection will be strongly predictive of increased aggression for both boys and girls.

Figure 3.3 Conceptual Model for the Relationship Between Childhood Aggression and Later Offending



In a meta-analysis of the empirical literature on risk factors for juvenile delinquency, Loeber and Stouthamer-Loeber (1986) find that variables related to parental socialization, such as *Parental Monitoring and Rule-Setting*, are among the most powerful predictors of juvenile delinquency. Family processes, and parenting processes in particular, are implicated by several criminological theories (Farrington, 1995; Simons, Simons and Wallace, 2004). Included among them are Sampson and Laub's (1993) age-graded control theory and Thornberry's interactional theory. For both, attachment to parents and parental socialization are key causal agents with respect to the original emergence of problem behavior. The work of Patterson and Yoerger (1993, 2002; see also Patterson, DeBaryshe and Ramsey, 1989) is also of particular relevance. They postulate that inept and coercive parenting potentiates the development of problem behavior in children. Boys who are subject to ineffective socialization at home are likely less receptive to socialization efforts at school, and therefore I expect that these boys will exhibit more serious and chronic aggressive behavior. The same expectation applies to girls as well, though there are comparatively few studies in the existing literature to support this hypothesis (c.f. Moffitt, Caspi, Rutter and Silva, 2001).

The conceptual model proposes that latent class membership based on aggressive behavior and further delineated by the specified covariates will significantly impact the probability of various measures of later offending. The right-hand side of figure 3.3 depicts these distal offending outcomes. The first relationship of interest is the link between patterns of aggression and involvement in juvenile offending. Research has established that latent classes depicting high, chronic, or escalating aggression are associated with a higher prevalence of offending. It is hypothesized that these findings will be replicated here. Given the normative nature of offending during adolescence, individuals on other trajectories may

have official records during adolescence. However, because these data are based on official records it is reasonable to expect that they do a better job of identifying those who are involved in delinquency to a more meaningful extent. This first component of the distal outcomes analysis model will identify an interesting group; those who engage in high-stable or escalating aggressive behavior during elementary school but do not go on to offend during adolescence. This group should be examined for the possibility that the discontinuity between their childhood and adolescent behavior reflects early desistance.

The continuity of antisocial behavior is most readily observed among those who exhibit the most serious behavior. The second component of the dependent variable, therefore, distinguishes violent from non-violent juvenile offenders. This will allow an examination of the relationship between early aggression trajectory membership and the seriousness of subsequent juvenile offending.

Examination of the relationship between early aggression trajectory membership and the age of onset of official juvenile offending will tap into the timing dimension of desistance. The inverse relationship between age of onset and desistance from offending is well established in high-risk samples (Elliott, 1994; Thornberry and Krohn, 2005), so age of onset may serve as a proxy, in a sense, for desistance. Those individuals who experience early onset are less likely to desist from offending during adolescence. It is hypothesized that members of the high stable and escalating aggression trajectories will experience earlier onset of juvenile offending. Again, however, those who do not experience early onset will be considered to be desisting in terms of the timing of their offending behaviors.

Finally, the conceptual model includes consideration of the pathways from childhood aggression to juvenile delinquency and on to adult offending up to age 26. Offending

behavior from ages 10 through 18 is posited to have a direct effect on adult offending, and the relationship between the development of childhood aggression and adult offending is hypothesized to be indirect and mediated by juvenile offending behavior.

Questions for Research

The review of literature presented in Chapters Two and Three motivated the conceptual model presented here. This model serves as an organizing framework for analysis of the specific research questions this study seeks to address. The overarching interest is in furthering our understanding of how the developmental course of aggression in early childhood influences later offending behavior, with particular interest in the pathways from childhood characteristics to desistance from offending. This general area of interest can be systematically addressed with a series of more focused questions, which are presented below.

The explanatory variable at the heart of this study is the development of aggression during elementary school. As such, a comprehensive description of the patterns of aggressive behavior observed in these data and the extent to which these patterns are shaped by covariates are prerequisites. Consideration of two preliminary questions accomplishes this task.

What patterns or trajectories of aggressive behavior are observed in these data?

An important first step is simply to describe the distinct longitudinal patterns of aggression that emerge in these data. Based on the review of existing research, I expect that a 3- or 4-class model will provide the best fit for the boys' data, with some combination of a chronic-high, moderate, and stable-low trajectory. For girls I expect that a 2- or 3-class

solution will best fit the data, with some combination of chronic-high, moderate, and stable-low trajectories. Although this question is designed primarily to generate the necessary information for addressing subsequent questions, it is important in its own right because it allows direct comparison of the differences and similarities, both qualitative and quantitative, in boys and girls development.

What is the relationship between aggression trajectory membership and early childhood antecedents of juvenile offending?

This question addresses the relationship between several theoretically derived predictors of problem and antisocial behavior and membership in each latent class. The covariates specified by the conceptual model are race, socioeconomic status, age, school readiness, peer rejection, parental monitoring and parental rule-setting. Again, the primary importance of this question is to establish the number and structure of patterns of aggressive behavior so that they explanatory power of these patterns can be explored. Nevertheless, the contribution of this question on its own should not be overlooked. First, this question facilitates further comparison of aggression in boys and girls. Second, if the influence of childhood aggression on desistance can be discerned, the relationship of these covariates to aggression will be of significant interest for policy and prevention.

What is the relationship between early childhood trajectory membership and the subsequent course of juvenile offending?

Here the analysis proceeds to an examination of the influence of aggression class membership on the distal outcomes of juvenile offending. To begin, an examination of the

relationship between class membership and a dichotomous measure of juvenile offending potentially identifies an interesting group – those who display persistent aggression during childhood (and would therefore be at high risk of later offending) but who do not actually offend during adolescence. A second dichotomous outcome will be examined for the subgroup that does offend during adolescence – whether a juvenile committed any violent offenses in the time period up to age 18. Next, I examine the relationship between trajectories of childhood aggression and a categorical outcome measure of the types of offenses, or crime mix. Finally, I address the question of whether time-to-onset of juvenile offending varies by aggression trajectory membership. The inverse relationship between the age of onset of criminal behavior and the seriousness and length of the subsequent criminal career has already been noted. If the development of childhood aggression is related to the age of onset of criminal behavior, age of onset may in turn be viewed as a mediating link between childhood aggression and desistance. I hypothesize that membership in a moderate or high aggression trajectory will significantly increase the risk of early onset of criminal behavior.

What is the relationship between the developmental course of aggression in early childhood and a measure of adult incarceration?

The next logical step after examining the relationship between childhood aggression and juvenile offending is to assess the relative strength of the relationship between childhood aggression and adult offending. The data for this study (described in-depth in Chapter Four) do not contain sufficient information on adult offending to directly assess desistance, but a dichotomous measure of adult incarceration provides an indication of the stability of antisocial behavior for a small portion of the data.

What is the relationship between the developmental course of aggression in early childhood and a measure of adult incarceration, once juvenile offending behavior is controlled?

The conceptual model proposes that the relationship between childhood aggression and adult offending is mediated by the developmental progression of behavior during adolescence and the later teen years. This question quantifies the mediating influence of juvenile offending so that any persistent effects of childhood development not accounted for by juvenile offending can be assessed.

Are any of these relationships conditioned by gender?

The final aim of this research is to gain a better understanding of how the patterns of aggressive behavior and the relationships of these patterns with distal outcomes (such as age of onset and components of desistance) vary by gender. To that end, each model is run separately for boys and girls so that differences in growth parameters and the predictive accuracy of trajectories on distal outcomes can be assessed.

Answers to each of these specific research questions have the potential to provide rich information and insight which extends our current understanding of the pathways from childhood aggression to desistance from adult offending. Analysis of these questions demands considerable data and modeling resources. Chapter Four describes the data and the analytic strategy capable of meeting these demands.

CHAPTER FOUR: DATA AND METHODS

The Data

Data for this research come from the first generation of the Johns Hopkins University Prevention Intervention Research Center's school-based interventions trials in Baltimore City Schools (hereafter referred to as the Baltimore Prevention Data) (Prevention Intervention Research Center, 2006). The sample was drawn for the purpose of evaluating two school-based interventions (for a complete description of sampling procedures and measures, refer to http:// www.jhsph.edu/prevention). Two successive cohorts of urban first-graders (in 1985 and 1986) were recruited from nineteen elementary schools, representing forty-three classrooms and five socio-demographically distinct areas of Baltimore. These geographic areas are defined by census tract and vital statistics data, and vary considerably by community composition and structure, though they were defined such that participants within each area were relatively homogenous with respect to ethnicity, housing, income, and family structure. The study participants are now approximately twenty-six years old. Assignment to experimental or control conditions in first and second grade was determined as follows: three or four schools from each of the five urban areas were selected, and each school then randomly assigned to receive one of the two interventions, or to serve as a control. Within the schools designated to receive an intervention, classrooms were randomly assigned to experimental or control conditions. Special education and gifted classrooms were excluded from the pool of eligible classrooms. The total sample from the two cohorts of first graders

contains data on 2,311 individuals. Four hundred fifty-two of these were randomly assigned to receive the Good Behavior Game intervention, and an additional five hundred twenty were designated to receive the Mastery Learning intervention. Only the control participants will be considered for the purposes of this research, as the interventions delivered to the experimental groups were designed explicitly to influence the development of aggression, which is to be used as the independent variable in this research. I would therefore expect some exogenous systematic differences in the course of childhood aggression between the experimental and control groups, the presence of which would unduly complicate the longitudinal study of aggressive/disruptive behavior. The control sample comprises 1,339 individuals. Of these, one hundred fifty-eight children are missing the fall of first grade Teachers Observations of Classroom Adaptation – Revised (TOCA-R) assessments. Because the fall of first grade assessment provides the baseline for estimating developmental trajectory membership, these cases must also be excluded from the analysis, resulting in a sample of 1,181. Finally, three individuals were missing information on one of the covariates to be employed in the analyses. Estimation of the effects of covariates on class membership with Mplus software requires complete data for all cases, so these three individuals are excluded as well, yielding a final sample of 1,178 students (51% male, 66% nonwhite), or 88 percent of the original control sample.

For both cohorts, data were collected in the fall and spring of first grade and in the spring of second through seventh grade. For cohort 1 only, data were also collected in the fall of second grade. An adult follow-up assessment was conducted at ages 19-20. A large portion of the transition from family to school socializing environments is captured in these data, which makes them particularly relevant for developmental research.

Measures

Independent Variable[6]*: Teacher Observation of Classroom Adaptation – Revised (TOCA-R; Werthamer-Larsson, Kellam and Wheeler, 1991)*

The TOCA-R is a structured interview conducted by a trained assessor that captures teachers' assessments of student behavior. The aggressive/disruptive behavior subscale of the TOCA-R provides the repeated observations of aggression required to construct a dynamic measure of childhood aggression, which can then be assessed in terms of its relationship with later behavior. Osgood and Rowe (1994) discuss the importance of using time-varying explanatory variables to understand change over time, and express surprise that such measures have not been employed in criminological research with greater frequency.

A general body of research demonstrates the reliability of teacher-rated behavior and the utility of these ratings for measuring the behavior of students when they are away from their parents (Cairns and Cairns, 1994; Harris, 1998; for example, see Greenberg et al., 1999). Further, research focusing specifically on teacher ratings of aggressive behavior finds them to be valid and reliable measures of aggression, with utility for predicting later antisocial outcomes (Campbell, Ewing, Breaux and Szumowski, 1986; Ensminger, Kellam and Rubin, 1983; Petras et al, 2004a; Petras et al, 2005). Teacher ratings of aggression have also provided the basis of assessment for a number of robust prevention evaluations (for example, Tremblay, Pagani-Kurtz, Masse, Vitaro and Pihl, 1995). Two studies with particular relevance for these data find support for the use of teacher reports of behavior.

[6] Upon introduction of the modeling strategy, TOCA-R aggression ratings are referred to as proximal distal outcomes, which implies dependent variable status. In the latent variable modeling framework, the observed indicators conceptualized as observable manifestations of a latent construct, hence use of the term outcome. In the larger conceptual framework of this research, however, aggression ratings are the basis for constructing the primary independent variable of interest – a dynamic measure of childhood aggression.

First, Epkins and Meyers (1994) found that teacher-parent convergence on aggression measures in an urban elementary school was significant for boys and girls. The second study examined concordance across multiple reporting sources, and found that inter-rater concordance was greatest for children ages six to eleven, and for externalizing rather than internalizing behaviors (Stanger and Lewis,1993). Thus, teacher ratings of behavior are widely accepted as valid and reliable, and the evidence specific to teacher assessments of externalizing behaviors among urban elementary school children endorses their use here.

Teachers assess students' aggressive behavior on a six-point scale (1=never true to 6=always true). The scale includes the following items: harms or hurts others physically, harms property, fights, stubborn, breaks rules, breaks things, yells at others, takes others' property, lies, teases classmates, and trouble accepting authority. Scores on each of these subscale item responses create the composite TOCA-R measure of aggressive/disruptive behavior for each child. Test-retest correlations for this subscale range from 0.65 to 0.79, and coefficient alphas range from 0.92 to 0.94.

Inspection of the specific items that constitute the aggressive/disruptive subscale reveals that it reflects behaviors extending beyond the discrete scope of physical aggression. A potential avenue for future research is an examination of only those specific items tapping into physical aggression. For this research, however, I retain the composite score. This decision is justified on empirical, substantive, and theoretical grounds. Broadband measures of aggressive/disruptive behavior are the basis of inquiry in much criminological research. In a review of research on aggression, Coie and Dodge (1998) extend their discussion to include antisocial behavior on the grounds that "the comorbidity of aggression with other antisocial behaviors suggests that an understanding of the etiology and

developmental course of aggression might be enhanced by including aggression into the broader class of antisocial behavior". Although Tremblay (2000) is troubled by Coie and Dodge's decision, he allows that it is consistent with the approach to studying childhood aggressive behavior over roughly the past thirty years. Analysis of the original composite score therefore facilitates an examination of how the results of this research are consistent with and expand upon existing research. Finally, as implied by Coie and Dodge's reasoning, the conceptualization of aggression as part of a broader class of antisocial behavior may generate important insight for theoretical perspectives on homotypic continuity of behavior. Finally, factor analyses conducted in previous research on these data (Werthamer-Larsson, Kellam and Wheeler, 1991) support a one-factor solution, meaning that when taken together, the individual items measured for the subscale tap into a single underlying (latent) dimension of problem behavior.

Table 4.1 reports mean aggression scores for each assessment period. Consistent with existing research, girls in the sample consistently display lower absolute levels aggressive/disruptive behaviors, and the ratings suggest very little change in levels of aggression from one assessment to the next. Boys in this sample evince increasing levels of aggression from first to third grade. Substantive interpretation of these patterns is premature, however, as the mean scores potentially mask the existence of heterogeneity of within-individual patterns.

Table 4.1 Mean TOCA-R Subscale Ratings, First through Third Grade

Aggression in:	Boys (N=597)	Girls (N=581)	Total (N=1,178)
Fall 1st Grade	2.01 (1.01)	1.70 (0.82)	1.86 (0.94)*
Spring 1st Grade	2.09 (0.99)	1.77 (0.85)	1.93 (0.94)*
Fall 2nd Grade	1.93 (1.02)	1.51 (0.67)	1.71 (.88)*
Spring 2nd Grade	2.26 (1.19)	1.75 (0.77)	2.00 (1.03)*
Spring 3rd Grade	2.33 (1.20)	1.75 (0.88)	2.03 (1.09)*

* Differences in gender means are significant at $p<0.05$
Note: standard deviations are reported in parentheses

Model Covariates

The proposed conceptual model presented in Chapter Three includes several covariates that are hypothesized to differentiate class membership. This earlier discussion also included the empirical and theoretical rationale for the place of each covariate in the model. This section describes the coding schema and decision rules applicable to each covariate, and presents descriptive information.

Table 4.2 reveals that the sample is essentially evenly divided between boys and girls, and that approximately two-thirds of the sample are Nonwhite. The measure for race is dichotomized into White/Nonwhite (1=Nonwhite) because there is insufficient variation in other racial groups to use a categorical measure[7]. The racial composition of the sample varies significantly by gender, Nonwhites accounting for 62 percent of the boys and 71.1 percent of the girls in the sample. *Eligibility for free lunch* (denoted by *lunch* in Table 4.2 and subsequent tables) provides a proxy measure of socioeconomic status. This is a dichotomous

[7] All but seventeen students in the sample are African or Caucasian (N_{Asian} =2, $N_{American\ Indian}$ =11, $N_{Hispanic}$ =4).

measure with 1 = eligible for subsidy. Just over half of the sample is deemed eligible according to their family income. Eligibility for boys and girls is statistically equivalent.

Table 4.2 Baltimore Prevention Project Control Sample Descriptives

		Boys (N=597) (50.7 %)	Girls (N=581) (49.3 %)	Total (N=1,178)
Race	nonwhite	370 (62%)	413 (71.1%)	783 (66.5%)
	white	227 (38%)	168 (28.9%)	395 (33.5%) *
Lunch	eligible	309 (51.8)	300 (51.6)	609 (51.7)
	not eligible	288 (48.2)	281 (48.4)	569 (48.3)
Age	<6.50	169 (28.3)	140 (24.1)	309 (26.2)
	>6.50	428 (71.7)	441 (75.9)	869 (73.8)
	mean	6.30	6.24	6.27*
Ready[a]	mean	3.15	2.83	2.991
	SD	1.28	1.21	1.26*
Reject[a]	mean	1.73	1.58	1.655
	SD	1.28	0.913	0.931*
Monitor[b]	low risk	0.715	0.850	0.787
	high risk	0.285	0.150	0.213
	mean	4.41 (sd = 1.61)	4.99 (sd = 1.42)	4.83 (sd=1.56) *
Rules[b]	low risk	0.400	0.474	0.439
	high risk	0.600	0.526	0.561
	mean	3.01 (sd = 1.85)	3.24 (sd=1.88)	3.14 (sd=1.87)

* Differences in gender means are significant at $p<0.05$

[a] Measured on a scale from one to six, with higher scores representing increasingly negative assessments, or higher risk.

[b] Values reported for low and high risk are proportions

Age is treated as a binary variable (1=less than six-and-a-half years of age at start of first grade). On average, boys are older than girls, but gender differences do not emerge in the dichotomized measure of age. School readiness (appearing in tables as *ready*) is measured with a subscale of the TOCA-R, and reflects teachers' overall assessment of a student's preparedness for school and adaptation to the academic environment. School readiness is

rated on a scale of one to six, with higher values denoting higher risk. In teachers' assessments, girls demonstrate significantly better adjustment to school than boys. This variable is normally distributed for boys and girls, so the original measurement scale is retained. Teachers also assess the extent to which students are *rejected* by their classmates on a six point scale, again with higher values corresponding to higher risk for adverse consequences. Girls are generally more accepted by their peers than the average boy. Previous analyses of these data demonstrate that teachers' assessments are significantly correlated with peer reports of rejection (Petras et al., 2004a). These ratings are normally distributed for boys and girls, so the original measure is again retained for the analyses. Data collected at the Young Adult follow-up interview provide measures of parental monitoring and parental rule-setting. The variable *monitor* comes from a question asking: "How much would you say that the people who took care of you while you were growing up kept tabs on where you were and who you were with?". Data for the variable *Rules* come from responses to the next question "How much would you say they set and enforced rules for you?". These items were rated on a scale of one ("not at all") to six ("very much"). The distribution of responses to these items was skewed, so both measures were cut at the midpoint. Girls recalled experiencing higher levels of parental monitoring than boys.

The Dependent Variable

The dependent variable of interest is official offending from ages 10 to 26. Measures of juvenile offending in the BPP sample come from police and court arrest and adjudication records of Baltimore City. Data were collected on the number, severity, and timing of

official arrests and convictions. Adult records were obtained from the Department of Corrections and include incarceration information through January of 2006.

Table 4.3 summarizes the official offending behavior of the sample. The police records and juvenile court data indicate that 229 of the 1,178 control participants, or 19.4 percent, experienced at least one arrest. One hundred six individuals have official records of three or more arrests, sixty individuals have records of five or more arrests, and the data reflect two individuals who have official records of fourteen arrests.

Offending outcomes will be analyzed according to five categorizations. The first is a simple dichotomous measure of offending. Second, among those who did commit at least one offense, do they have an official record of violent offending? Third, is there evidence of specialization by offense type? A categorical variable of crime mix provides the outcome variable for this question. Finally with respect to juvenile offending, do the identified latent classes differentially predict the age of onset of criminal behavior? Early arrest is the best predictor of long-term repeat offending (Farrington et al., 1990; Hanson, Henggeler, Haefele and Rodick, 1984; Loeber et al., 1991; Loeber and LeBlanc, 1998; Moffitt et al., 2001; Moffitt, 1993; Nagin and Farrington, 1992a; Tolan, 1987; West, 1982). Thus, the identification of a pattern of behavior in elementary school that significantly increases the risk for early onset is also then indirectly predictive of a long subsequent offending career.

Table 4.3 Official Offending Outcomes

		Boys n=597 (50.7 %)	Girls n=581 (49.3 %)	Total n=1,178 (100%)
Any official offending		161 (27)	68 (11.7)	229 (19.4)
# Offenses Committed	0	436 (73.0)	513 (88.3)	949 (80.6)
	1	45 (7.5)	40 (6.9)	85 (7.2)
	2	25 (4.2)	13 (2.2)	38 (3.2)
	3	23 (3.9)	6 (1.0)	29 (2.5)
	4	14 (2.3)	3 (0.5)	17 (1.4)
	5+	54 (9.1)	6 (1.0)	60 (5.1)
# Violent Offenses	0	464 (91.7)	533 (91.7)	997 (84.6)
	1	60 (10.1)	28 (4.8)	88 (7.5)
	2	27 (4.5)	11 (1.9)	38 (3.2)
	3	16 (2.7)	3 (0.5)	19 (1.6)
	4	13 (2.2)	2 (0.34)	15 (1.3)
	5+	17 (0.28)	4 (0.69)	21 (1.8)
Offense Mix				
Any offense		161 (27.0)	68 (11.7)	229 (19.4)
Mixed offenses		91 (15.2)	18 (3.1)	109 (9.3)
Violent Only		42 (7.0)	30 (5.2)	72 (6.1)
Non-violent only		28 (4.7)	20 (3.4)	48 (4.1)
Any violent offense		133 (22.3)	48 (8.3)	181 (15.4)
Age of Onset	Mean (s.d.)	14.41 (2.03)	14.02 (1.91)	14.20 (2.00)
	<10	8	3	11
	10	3	1	4
	11	5	3	8
	12	10	12	22
	13	40	16	56
	14	32	13	45
	15	23	9	32
	16	29	7	36
	17	10	4	14
	18	1	0	1
Adult Incarceration	N=1178	97 (16.2%)	6 (1.0%)	103 (8.7%)
	N=229	60.2%	8.8%	45.0%

Adult offending is reported as a dichotomous measure of whether an individual experienced a term of incarceration under the Department of Corrections. Of the 229 juvenile offenders, 103 (45.0 percent) experienced a term of correctional confinement.

Missing Data

Attrition is endemic to longitudinal studies such as this (Hansen, Tobler, and Graham, 1990), and missing data are an inevitable consequence of attrition. Each of these models will be tested on the Baltimore Prevention Data in Mplus software using full information maximum likelihood estimation and assuming that data are missing at random (MAR) (Muthén, 2004b). MAR assumes that data are either missing at random with respect to the outcome of interest, or random after other measured variables are incorporated into the analysis (Muthén, 2001, 2004b; Schaeffer et al, 2003). Mplus software generates a covariance coverage matrix, which gives the proportion of observations available for each indicator variable. The minimum proportion required for model convergence is .10 (Muthén, 2004b). In the present study, the lowest coverage is .40, indicating that the data are more than sufficient for estimating the proposed models.

Analytic Strategy

The goal of this research is to further our understanding of how the development of aggression in childhood influences the later process of desistance from offending. More generally, this is a question of the effects of early development on individual change over

time. As such, it requires a model specified at the individual level (Land, 1992), and with an explicit longitudinal component. The study of within-individual change over time has perhaps been hampered by limitations of the methodological tools at our disposal thus far. Ordinary regression techniques are commonly applied in the social sciences and criminology, and often are an appropriate strategy for assessing the effects of static risk factors. These techniques, however, require an assumption of independence among observations. Certainly, this assumption does not hold when the observations of interest are repeated measures on an individual over time.

Evolution of Modeling Strategies

A variety of modeling strategies have emerged in attempts to address this methodological issue. Early efforts at disaggregating the age-crime curve involved subjective classification of individuals into groups according to some articulated criteria, an approach commonly referred to in the literature as *ex ante* assignment. Although this classification approach has the potential to identify similar groups as those identified by more advanced forms of analysis, the inability to explicitly test for the existence of distinct classes and to distinguish random from meaningful variation renders it quite limited (Fergusson, Horwood and Nagin, 2000; Nagin, 2005).

Raudenbush and Bryk (2002; see also Bryk and Raudenbush, 1992) advocate the application of a multilevel or hierarchical linear model (HLM) to questions of within-individual change. They propose that these models account for heterogeneity by identifying a mean pattern of development and then estimating random effects for the intercept and slopes around the mean regression line. These random effects serve as individual-specific growth

factors (Muthén and Muthén, 2000). A potential limitation of this type of model, generally referred to as a Conventional Growth Model (CGM), lies in is the assumption that variation in individual differences is normally and continuously distributed around this single mean pattern. Few existing criminological theories explicitly comment on the theoretical validity of this assumption, and mounting empirical evidence to refute it compels consideration of alternative strategies.

Latent Class Growth Analysis

A class of strategies broadly classified as Latent Class Growth Analysis (LCGA) offers one such alternative. Rather than imposing a priori assumptions as to the shape (or shapes) of the underlying distribution in the population, these methods test for clustering of individuals around distinct behavioral patterns or trajectories (Blokland, Nagin and Nieuwbeerta; Jones, Nagin and Roeder, 2001; Nagin, 2005). A latent class model is then derived in which each group is described by a categorical latent variable with unique growth parameters defining the shape of the growth curve (Muthén, 2004a; Muthén and Muthén, 2000). LCGA is a flexible modeling strategy in its absence of parametric assumptions about the population. However, it does place some restrictions on the nature of the estimated latent classes. Growth parameter variances associated with each latent class are constrained to zero, which means that individuals within a trajectory are constrained to the same slope and intercept. By implication, all of the individual variability in development is accounted for by class membership, and residual variation seen as random error. This inability to estimate within-class variation limits the utility of the model in two important ways: First, because within-class variation cannot be modeled, it is likely reflected in the model as between-group

variation, which potentially results in the identification of more classes (Nagin and Tremblay, 2005). Bauer and Curran (2004) argue that this addition of spurious classes forced by the assumption of within-class homogeneity renders the model doubly misspecified, because in addition to the incorrect number of groups, the class structures within each class are different. Second, class membership is described only by a mean intercept and slope, which limits tests of the association of class membership with antecedents and distal outcomes. Research is needed to examine the implications of these limitations, in terms of the patterns of behavior identified and the relationship of trajectory group membership to later behavior. Bauer and Curran (2003a) suspect that these models are frequently invoked for the sake of ease and efficiency, and that those who explicitly test the validity of the assumptions reject them in favor of other alternatives.

A final alternative modeling strategy, Growth Mixture Modeling (GMM) is similar in many respects to LCGA, but with important extensions. Similar to LCGA is the notion that repeated measures of an observed behavior reflect a finite number of latent trajectory groups. The divergence from LCGA is that GMM allows but does not assume within-class homogeneity (Muthén and Muthén, 2006; Muthén and Shedden, 1999). Variation within classes also allows for more sensitive tests of the relationships of covariates with latent classes. Because GMM allows increased flexibility in model specification, it provides an ideal modeling strategy for the research questions at hand. The next section further details the specifics of the models.

Growth Mixture Modeling

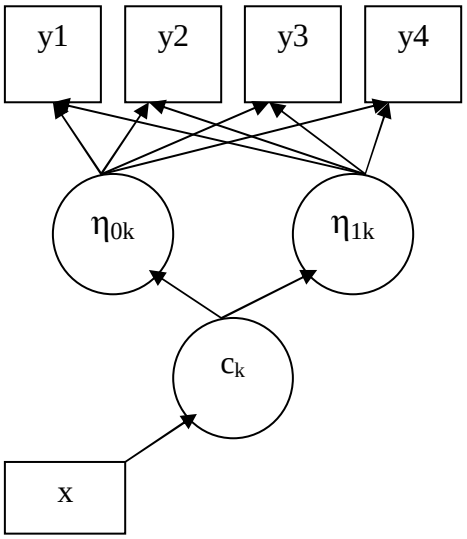
GMM is a developmentally meaningful approach to the analysis of longitudinal data (Muthén, 2003). Growth Mixture Modeling derives its flexibility from a synthesis of aspects of LCGA and CGM. A separate growth curve is estimated for each identified group within the population by the same latent variable approach used in LCGA. The categorical latent variable representing class membership remains, but is now complemented by the estimation of a continuous latent variables capturing growth factor variances, as is done in CGM. This second step allows for intra-class heterogeneity (Muthén, 2004).

Figure 4.1 provides a simple visual representation of GMM. Repeated measures y_t of observed indicators – in this case, aggression – are used to identify a categorical latent variable c_k (class membership) with slope and intercept and slope, η_{0k} and η_{1k}, respectively. The subscript *k* indicates that these latent variables are class-specific. The slope and intercept parameters are the random growth factors that determine the starting point and shape of longitudinal development associated with each class.

GMM can also accommodate consideration of covariates thought to be related to class membership; these are represented by x. Theoretically and empirically supported covariates included in the models are race, eligibility for free lunch (as a proxy for socioeconomic status), age at the start of first grade, teacher assessments of academic readiness and peer rejection, and a retrospective measure of each child's assessment of parental monitoring and rule setting. Covariates serve two purposes in these models (Muthén, 2004a). First, the probability of membership in a given trajectory may be conditioned by a covariate. Including such covariates in the model, then, allows for more precise and accurate class assignment. Second, the use of covariates also allows for early identification of class membership, as

conditional probabilities of class assignment can be computed based on combinations of covariates.

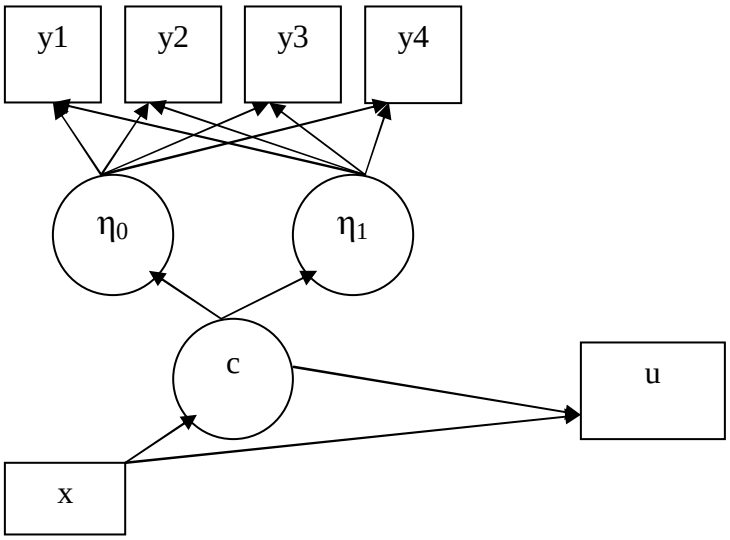
Figure 4.1 Growth Mixture Model



General Growth Mixture Modeling (GGMM) is an extension of GMM that allows for prediction of a distal outcome, u, based on trajectory membership (Muthén, 2004a; Muthén and Muthén, 2000). Figure 4.2 illustrates the extension from GMM. The figure is identical to Figure 4.1 in its representation of the latent class growth model. The addition of an outcome, u, distinguishes this from the basic growth mixture model.

To investigate the presence of different class trajectories in the latent class analysis component of the model, Mplus formulates a finite-mixture random effects model where the trajectory classes are captured by a latent class variable with *K* classes (Muthén, Brown, Masyn, Jo, Khoo, Yang, Wang, Kellam, Carlin and Liao, 2002; Muthén and Shedden, 1999).

Figure 4.2 General Growth Mixture Model



For individual *i* in class *k* (*k* = 1,2,…, K), the growth mixture model is given by:

$$y_{it} = \eta_{0i} + \eta_{1i}\, a_t + \eta_{2i}\, a_t^2 + \varepsilon_{it}$$

$$\eta_{0i} = \alpha_{0k} + \gamma'_{0k} x_i + \zeta_{0i}$$

$$\eta_{1i} = \alpha_{1k} + \gamma'_{1k} x_i + \zeta_{1i}, \qquad \text{where}$$

y_{it} are repeated measures on observed outcomes (i = 1, 2,…, *n*; t = 1,2,…, T), η_{0i}, η_{1i} and η_{2i} are class-specific growth factors, a_t is the time variable set at 0 for initial status, and ε_{it} is the residual term, which may vary across trajectory classes. Allowing the means, variances and covariances of η_{0i} and η_{1i} to vary creates the different trajectory classes, and the variance of

the residual term may also vary across classes. Covariates (x) may influence class membership and may have differing influence on class-specific growth factors.

When including a dichotomous distal outcome, u, predicted by trajectory membership in a GGMM framework, class membership influence is calculated with the logit regression:

$$\Pr(u_i = 1 | c_i = k, x_i) = 1/(1 + e^{\tau\kappa - K\kappa \boldsymbol{x}_i})$$

where the influence of class membership (*c)* on a distal outcome (u) is found in the class-varying thresholds (τ_κ) and slopes for covariates (x) which are captured by the parameter K_κ (Muthén, 2004a). This is an extension of the standard multinomial logit model.

Assessing Model Fit

The challenge of identifying the appropriate number of classes to account for unobserved heterogeneity has been the subject of much discussion and research. Complicating the issue is the absence of any absolute criterion or universally accepted threshold value against which to assess a latent class growth model. Such relativity is the boon and the bane of longitudinal methods for latent variables; the flexibility afforded comes at the cost of some inherent subjectivity in model selection. Ideally, the "best" model is selected on the basis of a complement of statistical and substantive considerations.

The appropriate number of trajectory classes is rarely known prior to model specification, so the traditional approach to model building begins with specifying a number of different class solutions and assessing their relative fit. Models with different numbers of classes are non-nested (D'Unger, Land, McCall and Nagin, 1998), so the χ^2 likelihood-ratio statistic that frequently guides model selection decisions is no longer appropriate. A number

of alternative fit statistics provide the basis for model selection. The Bayesian Information Criterion (BIC; Kass and Raftery, 1993; Schwarz, 1978) is calculated by log(L) - 0.5 * log(n) * k , where L is the model maximum likelihood, n is the sample size, and k is the number of parameters in a model. Smaller values of the BIC statistic are better. The Lo-Mendell-Rubin statistic is an adjusted likelihood ratio test (ALRT; Lo, Mendell and Rubin, 2001) for H_0 K-1 classes, where a p-value less than 0.05 indicates acceptable fit. Entropy (Ramaswamy, Desarbo, Reibstein and Robinson, 1993) is a summated measure of classification accuracy; that is, how well the estimated model performs with respect to identifying the most likely class membership. The final formal test for statistical fit is the Bootstrapped Likelihood Ratio Test (BLRT), which provides a superior test of fit than a naïve likelihood ratio test by applying the estimated model parameters to bootstrap samples and testing the LRT for each (Feng and McCulloch, 1996). Ideally these fit statistics will point toward the same class solution as the most faithful characterization of the data. Lack of consensus among them, however, is not necessarily problematic, as each is calculated based on slightly different "rewards" for maximizing likelihood and "penalties" for the number of estimated parameters (Bauer and Curran, 2004).

In addition to these formal statistical tests, estimated models should also be assessed with respect to parsimony and the size of the specific classes identified. For example, a six-class model may provide better statistical fit in the strict sense of these formal tests, but if the additional class contains a trivial portion of the sample and fit indices suggest that a five-class solution provides a reasonable fit, selection of the six-class model demands a more compelling justification than a lower BIC or higher entropy. Substantive, conceptual, practical and theoretical considerations may provide such justification. Whether expressed as

support for statistical conclusions or as reason to override convention, substantive criteria are an essential component of model assessment, and should not be neglected, even in the face of "ideal" statistical fit.

Potential Vulnerabilities of Growth Mixture Models

As is true for any quantitative strategy for modeling behavior, appropriate application of GMM requires an understanding of the assumptions of the model and due consideration of potential sources of misspecification. Bauer and Curran (2003a), for example, urge researchers to exercise caution when the application of GMM is intended to describe population heterogeneity and subsequently identify the relationships of covariates with distinct subgroups. In considering the statistical theory underlying finite normal mixture models, they realized the potential of GMM to extract more than one class from data comprised of a single homogenous population. This issue surfaces when the distribution of the repeated measures is non-normal. A GMM fit to this distribution will likely view the non-normality as the consequence of aggregating two or more distinct subgroups, which may in fact be the case. It may also be the case, however, that a non-normal distribution of aggregated data simply reflects a homogenous group following a non-normal distribution function. Fit statistics and model assessment criteria are not sensitive to this distinction, so selection of the appropriate model must rely on theoretical guidance. To investigate the extent of this problem, Bauer and Curran conduct a simulation study on non-normally distributed data generated as though from a single, homogenous population. Estimation of a 2-class GMM on these data converged every time. More troubling is Bauer and Curran's finding that for the majority of the GMM fitted to non-normal data, fit statistics actually

endorse the multiple-class solution over a single class. Upon the identification of a multiple class model, applied researchers frequently turn to an assessment of the relationship of covariates with growth parameters or class membership. Bauer and Curran urge caution here as well, based on their finding that estimation of a multiple class model on a homogenous group diminishes power to detect the true influence of covariates on the aggregate data.

Muthén (2003) answers Bauer and Curran's critique of GMM and offers two primary points of mitigation. First, while Bauer and Curran characterize the non-normality of their simulated data as mild, in Muthén's assessment the data are "strongly non-normal" (p. 369) and therefore would not likely be subject to GMM in the first place. Second, Bauer and Curran point to the lack of empirical tests to determine whether a well-fitting multiple class model should be selected over a well-fitting aggregated population model. In response, Muthén reports that the emergence of the Lo-Mendell-Rubin likelihood ratio test addresses this concern. Muthén's ultimate assessment of Bauer and Curran's critique is that their scrutiny is important and timely for deterring "poor applications" (p. 369) of the modeling strategy, but the critiques they offer are not particularly damaging. In their brief response, Bauer and Curran (2003b) maintain that their simulation data was modest in non-normality and highly consistent with the data analyzed in much psychological research.

Hipp and Bauer (2006) identify a second issue that requires consideration when GMM models are estimated. They note the susceptibility of finite mixture models to singularities and multiple optima of likelihood functions, and wonder whether GMM is similarly affected. As an extension of finite mixture models, one might expect similar erratic behavior of likelihood functions for GMM. Alternatively, the addition of growth parameters in GMM imposes a structure on the estimated class means and covariances, which may

insulate against local solutions to some extent. Hipp and Bauer assert that this is a question worthy of systematic examination. Results of their case study and a Monte Carlo simulation indicate that local optima are a serious consideration for GMM. Models seems to be particularly sensitive to start values in the Mplus framework, which uses maximum likelihood estimation and the expectation-maximization (EM) algorithm. Model complexity and the number of latent classes also influence the chances of convergence on a local solution, or nonconvergence. A comparison of the substantive results generated by the global solution model to those from a local solution provides a dramatic picture of the consequences of choosing a model based on local optima – the resulting models are quite different. Based on their systematic investigation of local optima with GMM, Hipp and Bauer assert – and one would be hard pressed to disagree – that a thorough examination of likelihood surfaces is required. They close with three specific recommendations for estimating GMM. First, researchers should vary start values – extensively, in the case of complex models with many parameters. Hipp and Bauer recommend using at least 50 to 100 start values. Second, various solutions should be compared in order to determine the stability of the model. Consistent substantive results from the best solutions should be observed. Third, consideration of the frequency of the solution with the highest log likelihood provides a diagnostic tool; infrequent convergence of start values at the optimal solution should prompt closer examination of a model for possible misspecification. Hipp and Bauer remain optimistic about the contribution of GMM and its ability to elucidate heterogeneity in change over time. The addition of their recommendations for avoiding local optima contributes to the appeal of GMM for the analyses at hand.

CHAPTER FIVE: RESULTS

Introduction

Results of the application of the analytic strategy described in Chapter Four are presented here. The first section describes the estimation of growth mixture models to capture heterogeneity in the developmental course of aggression for elementary school-aged boys and girls. Upon identification of the best models, the relationships between antecedent covariates and the trajectory groups identified by the models are discussed. The discussion then moves to the relationships of trajectory groups to several distal outcomes measuring offending behavior. Each section first presents the findings for boys, followed by the findings for girls.

What is the relationship between aggression trajectory membership and early childhood antecedents of juvenile offending?

Model building begins with estimation of a traditional single-class growth model to determine the functional form of the development of aggressive/disruptive behavior from Fall of first grade through Spring of third grade. Table 5.1 provides a summary of fit statistics for an intercept-only model (I), an intercept-slope model (IS), and an intercept-slope-quadratic slope model (ISQS). The results of the first round of model estimation are shown in the shaded portions of the table. For comparisons of nested models such as these, the $\chi 2$ statistic provides the appropriate test for fit. In this case, for both boys and girls, the IS model

is nominated as the best fit. Once the appropriate model is selected, the other fit indices may be consulted to further evaluate the model.

Table 5.1 Comparison of Single Class Growth Models

	Boys (n=597)			
Fit Indices	I	IS	ISQS[a]	Modified IS
$\chi 2$ (df)	213.639 (13)*	95.667 (10)*	62.096 (6)*	30.912 (9)*
CFI[b]	.785	.908	.940	.977
TLI[b]	.835	.908	.900	.974
RMSEA[c]	.161	.120	.125	.064
SRMR[c]	.151	.072	.078	.046
	Girls (n=581)			
$\chi 2$ (df)	227.506 (13)*	147.733 (10)*	60.345 (6)*	53.527 (9)*
CFI	.776	.856	.943	.953
TLI	.828	.856	.905	.948
RMSEA	.168	.154	.125	.092
SRMR	.141	.121	.062	.043

* Significant at $p<0.05$

[a] Estimation of this model did not produce a positive definite residual covariance matrix for boys or girls

[b] Desired value is >.95

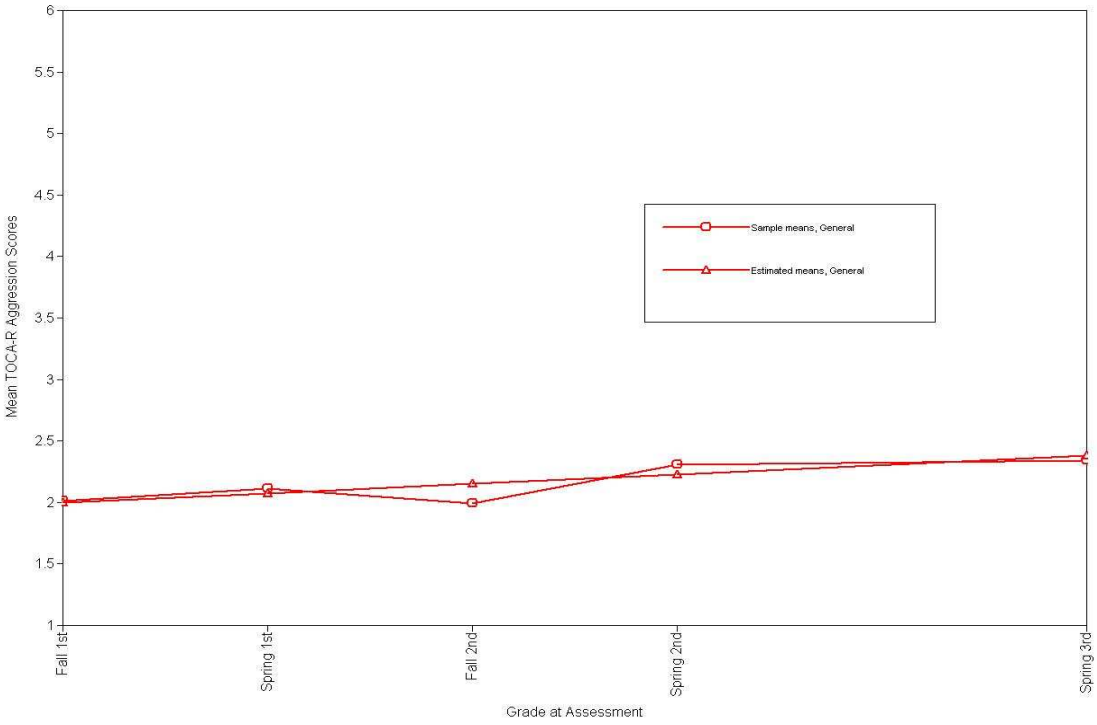
[c] Desired value is <.06

None of the models reach the desired value of CFI, TLI > .95, but at 0.908 for boys and 0.856 for girls, these indices for the IS models suggest an acceptable fit. The same is true for the values of the Root Mean Square Error of Approximation (RMSEA) and the

Standardized Root Mean Square Residual (SRMR), both of which should ideally fall below .06. These fit statistics are acceptable, but not ideal. Modification indices are therefore consulted for guidance as to how the IS model may be adjusted in order to provide the best fit. For both boys and girls, modification indices suggest that there is a correlation between aggressive/disruptive behavior ratings in the Fall and Spring of first grade, and in the Fall and Spring of second grade, and that the model may be improved if it is specified to account for

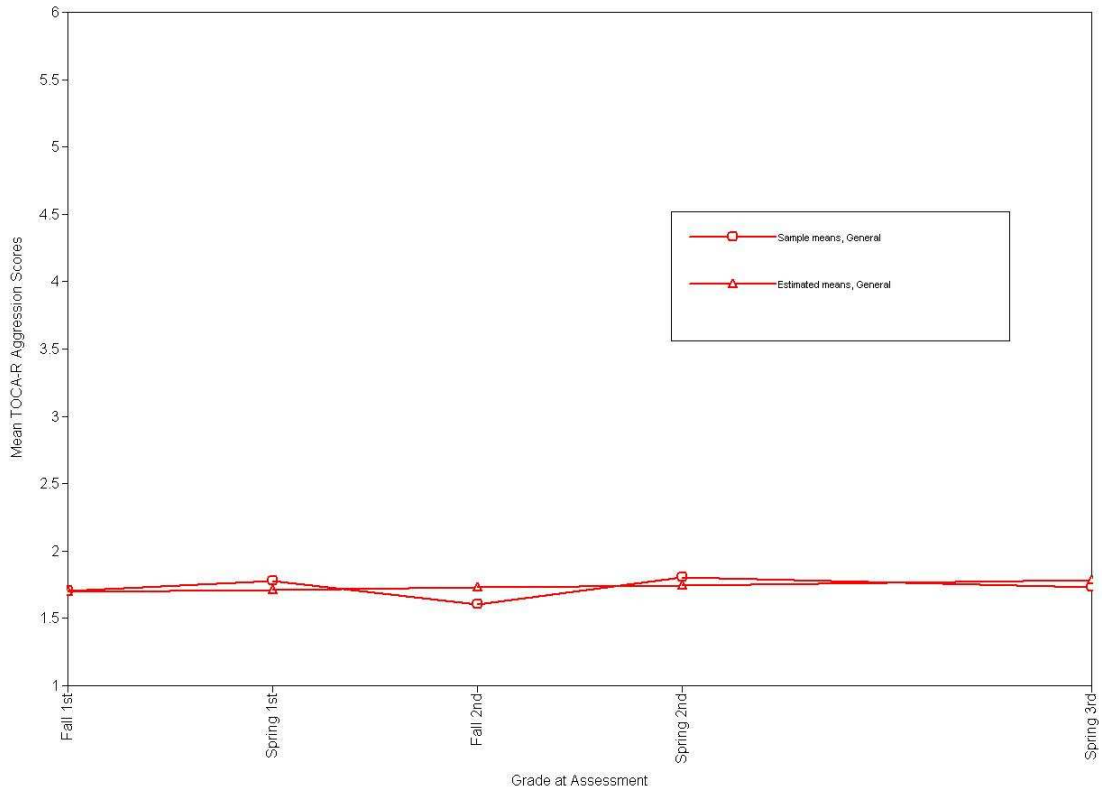
this correlation. This model specification is substantively supported, as the same teachers rated students' aggressive/disruptive behavior at both assessment points for first and second grades. Examination of model results for males and females also indicates that the correlation between the intercept and the slope, though significant, is negligible in size (r= -0.165 and -0.109, respectively) and therefore may be fixed at zero. An intercept-slope model for boys and girls is estimated, now allowing for the observed correlations between behavior ratings and the slope-intercept correlation set to zero. These modified IS models yield improved fit for both boys and girls, evidenced by the improvement on each of the fit statistics outlined above. Model fit is sufficiently improved to allow the conclusion that when a single-class growth model is estimated, an intercept and linear slope growth parameter are capable of capturing the development of aggressive/disruptive behavior over time. Recall, however, that this traditional growth model assumes that the sample is drawn from a single population, such that one class or group is capable of capturing heterogeneity in development over time through the estimation of random effects or growth factors. If tests of this restriction suggest that it is tenable, the single-class model provides a parsimonious and relatively straightforward estimation technique. If the assumption of a single and largely homogenous population is invalid, however, then the single-class model presents an oversimplified representation of the data and ultimately is of little use for theoretical development or practical application. Assessing the suitability of this model, then, becomes an important task, and one we may begin to address with a simple visual inspection of the observed means of behavior plotted with the predicted means generated by the model.

Figure 5.1a Observed and Estimated Means: Single Class Growth Model – Boys (n=597)



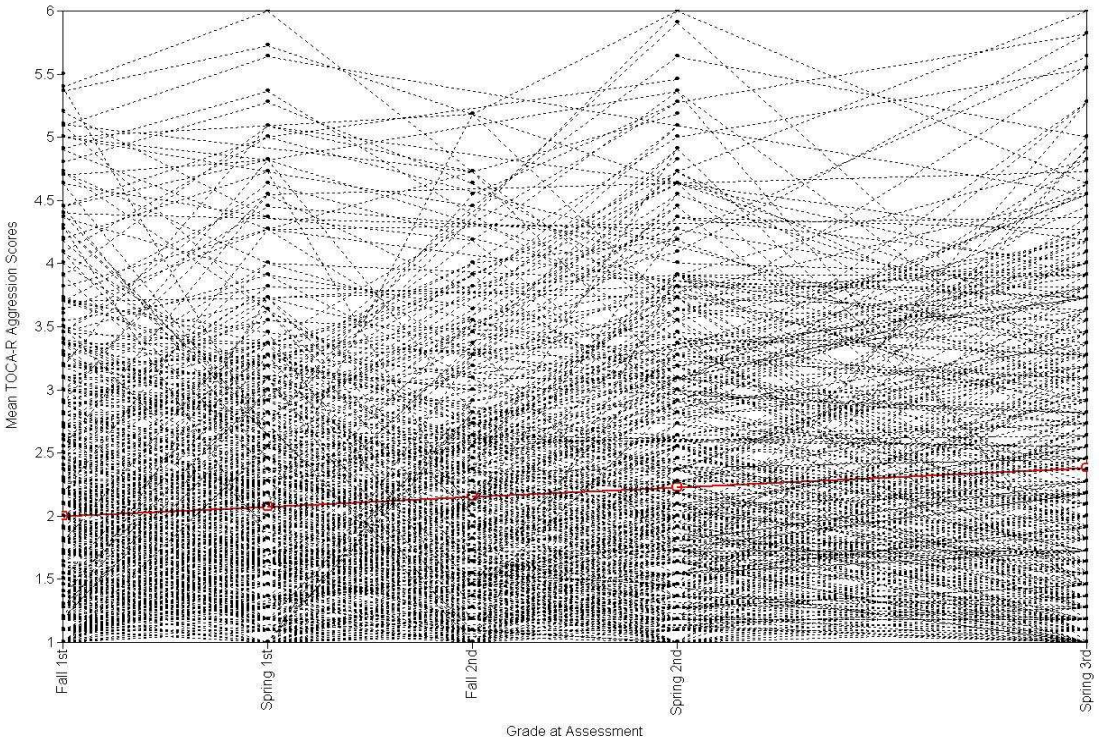
Figures 5.1a and 5.1b shows the observed sample mean of aggressive/disruptive behavior ratings plotted with the means estimated by the single-class growth model for boys and girls, respectively. Although the single-class model at times underestimates (e.g. Fall of second grade) or overestimates (Spring of second grade) the observed levels, it appears that the predicted means provide a reasonably close approximation of the observed sample means.

Figure 5.1b Observed and Estimated Means: Single Class Growth Model – Girls (n=581)



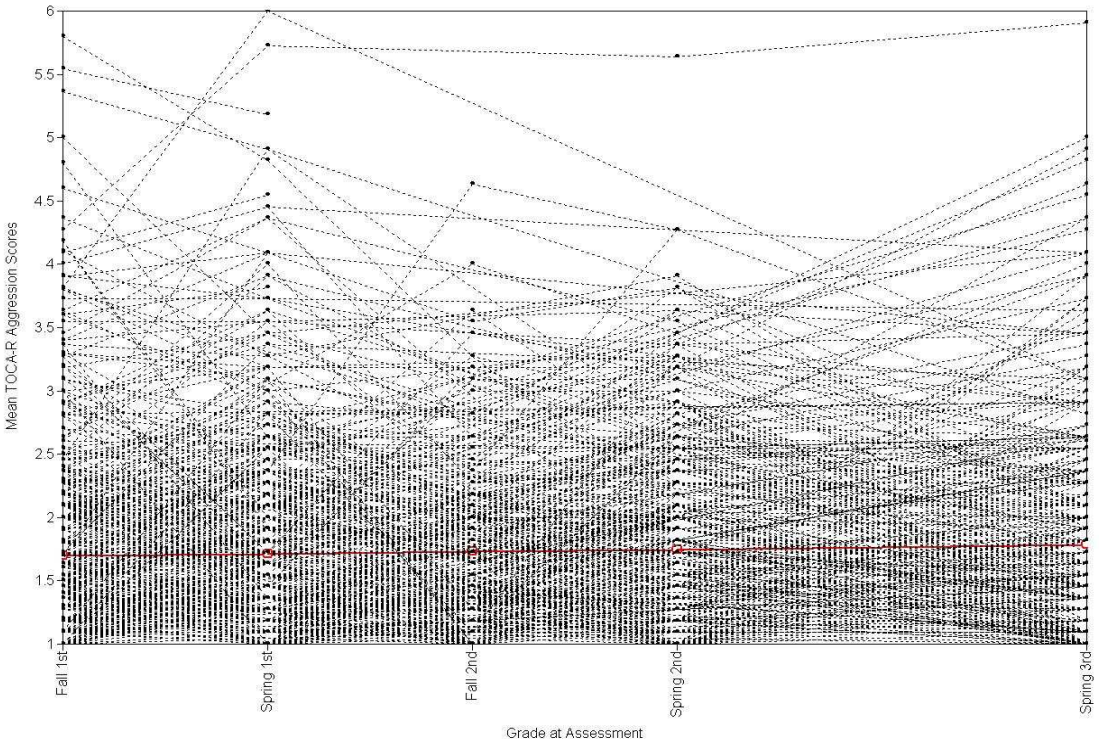
A different picture emerges when the estimated mean of aggressive/disruptive behavior is plotted with individual-level patterns instead of the sample means. Figures 5.2a and 5.2b show the considerable variation around the mean predicted by the single-class models. The estimated means of aggressive/disruptive behavior in the aggregate belie the notable heterogeneity observed at the individual level, with respect not only to initial levels of the behavior, but also the shape of development over time.

Figure 5.2(a) Estimated Means and Observed Individual Values for Single Class Growth Model – Boys (n=597)



The limitations of the CGM for exploring individual differences in development motivate the next model stage in the analysis, which is the application of a modeling strategy capable of empirically identifying unique longitudinal patterns within the sample. A number of latent class growth modeling strategies are available for this purpose, with semi-parametric growth models (SPGM; Nagin, 2005; Nagin and Tremblay, 1999) as the most parsimonious. Although these models are designed to identify heterogeneity in development, they impose the assumption that identified trajectories comprise homogeneous groups of individuals.

Figure 5.2(b) Estimated Means and Observed Individual Values for 1-class Growth Model – Females (n=581)



Given the lack of theoretical consensus on this issue, this assumption requires empirical examination. Appendix A provides a complete description of this examination and of the model building procedure. Ultimately, I determined that General Growth Mixture Modeling (GGMM) is best equipped for the analyses at hand.

I applied GGMM to the longitudinal measure of aggressive behavior from first through third grade to identify unique patterns of behavioral development. The single-class growth model (as discussed above) established that the appropriate functional form of the underlying growth process for the whole sample is an intercept-slope model. The adjustments to the single-class model are also incorporated here: residual variances of aggressive behavior for the Fall and Spring of first and second grade are allowed to co-vary because the same

teachers rated students' behavior for the two assessments during each school year, and the parameter estimate for the slope-intercept correlation is fixed at zero[8]. Following Muthén et al. (2002), I estimated 2, 3, 4, 5 and 6-class solutions to obtain the information criteria required for model comparison and selection.[9]

Patterns of Aggressive Behavior in Boys

Table 5.2 reports the model fit indices for the 2- through 6-class solutions for boys. The fit indices most strongly endorse a 4-class solution to describe boys' patterns of aggressive behavior, but fit indices for the 3-class solution are acceptable, so the 3-class model also warrants further consideration. The estimated model parameters and modification indices are consulted to ascertain what adjustments may be appropriate and if they result in improved substantive and statistical fit. Modification indices for the 3-class solution suggest that the residual variances associated with class three – the non-aggressive group - may differ from those in the other classes. This is consistent with the reasonable notion that boys in the non-aggressive class show less variability in their aggressive behavior than boys in other classes, so the model is specified to allow the class three residual variances to differ from those for classes one and two. Similarly, modification indices suggest freely estimating the intercept variance for the non-aggressive class. This modification is also reflected in the re-estimated model. Results of this model specification are reported as model 3.1 in Table 5.2.

[8] These modifications indices were also incorporated in previous analyses of these data (Petras et al, 2004; Schaeffer et al., 2003, 2005).

[9] In accordance with Hipp and Bauer's (2006) recommendations to avoid the possibility of local maxima, the random perturbations of initial start values are increased from the default of ten to one hundred, with ten final stage optimizations instead of the default of one. In addition, twenty iterations of each set of start values are allowed in the initial stage of optimization instead of the default of ten. This procedure is applied to all GGMM models from this point forward.

Table 5.2 Fit Indices for Latent Class Solutions: Boys (n=597)

Base Models[a]							
Latent classes	LL	df	BIC	SSABIC	Entropy	ALRT	BLRT
2	-2994.107	23	6135.228	6062.210	0.853	0.0665	0.000
3	-2938.543	33	6088.020	5983.255	0.770	0.0007	0.000
4	-2887.449	43	6069.751	5913.239	0.881	0.0123	0.000
5	-2879.556	53	6097.884	5929.625	0.779	0.3060	0.000
6	-2843.524	63	6089.740	5889.733	0.805	0.2366	0.040
Modified Models							
3.1	-2715.317	39	5679.919	5556.106	0.879	0.013	0.000
3.2	-2717.331	37	5671.164	5553.700	0.880	0.08	0.000
4.1	-2700.518	44	5682.281	5542.594	0.792	0.0650	0.000
4.2	-2701.278	43	5677.409	5540.896	0.791	0.176	0.000

[a] Base models free the parameters for the correlation of TOCA-R scores in Fall and Spring of 1st and 2nd grade, and the correlation of the growth factors (slope-intercept) is set to zero

The modifications result in a better-fitting model, with all fit statistics exceeding the criteria for acceptable fit. Further examination of the model results reveals two additional changes in model specification worth pursuing. First, the parameter estimates for model 3.1 include a negative residual variance associated with the TOCA-R rating in the Fall of first grade. The estimate is small and non-significant (β = -0.008, s.e.=0.007), so the residual variance for this parameter is set to zero for the non-aggressive class. Finally, the correlation of aggression ratings in the Fall and Spring of first grade are persistently small and non-significant as well, (β = -0.005, s.e.=0.005), so this parameter is set to zero. These final modifications yield the best fitting 3-class solution, reported as model 3.2 in Table 5.2.

The same recommended modifications to the base model emerge for the 4-class solution as for the 3-class – freeing the residual variances and the intercept variance for the non-aggressive class. These modifications are reported as Model 4.1 in Table 5.2. Although

the BIC and SSABIC drop, the entropy (0.792) and the ALRT statistic (0.0650) indicates that this modified model is an unacceptable fit. Returning to the modification indices generated in the 4-class base model, a reasonable alternative is to estimate the model with the intercept variance for the non-aggressive class constrained to zero. This model is reported in Table 5.2 as Model 4.2. Again, model fit worsens. The best fitting model among the 4-class solutions remains the base model. The choice of the best final model, then, lies between the modified 3-class solution and the original 4-class solution. Fit indices and parsimony both favor the 3-class model. I turn now to a discussion of the patterns of aggressive behavior among boys identified by this final model.

The best fitting model for boys identifies three distinct trajectories of aggressive behavior. Table 5.3 summarizes the estimated model parameters and fit indices. Thirteen percent (n=77) of the boys in the sample are most likely to be in Latent Class 1, which can best be described as a High-Declining (HD) behavioral trajectory. These boys exhibit high levels of aggressive behavior in the Fall of first grade ($\alpha = 3.939$, s.e. = 0.167) and consistently decrease in aggression through third grade ($\beta = -0.373$, s.e. = 0.114). The largest group of boys (n=390, 65%) are those most likely to be in Latent Class 2. Boys in this trajectory show a Moderate-Increasing (MI) pattern of aggressive behavior. On average, these boys were rated 1.951 (s.e. = 0.072) on the TOCA-R scale in the Fall of first grade, and each subsequent assessment saw an average 0.211 (s.e. = 0.041) increase in their aggression rating. Finally, Latent Class 3 describes a Low-Increasing (LI) trajectory of 130 boys who comprise 22 percent of the sample. Boys in this class are essentially considered non-aggressive by their teachers ($\alpha = 1.049$, s.e. = 0.020), though the slope estimate ($\beta =$

0.200, s.e. = 0.083) indicates a slight increase in aggression from first through third grade. Figure 5.3 provides a graphical representation of the 3-class solution for boys.

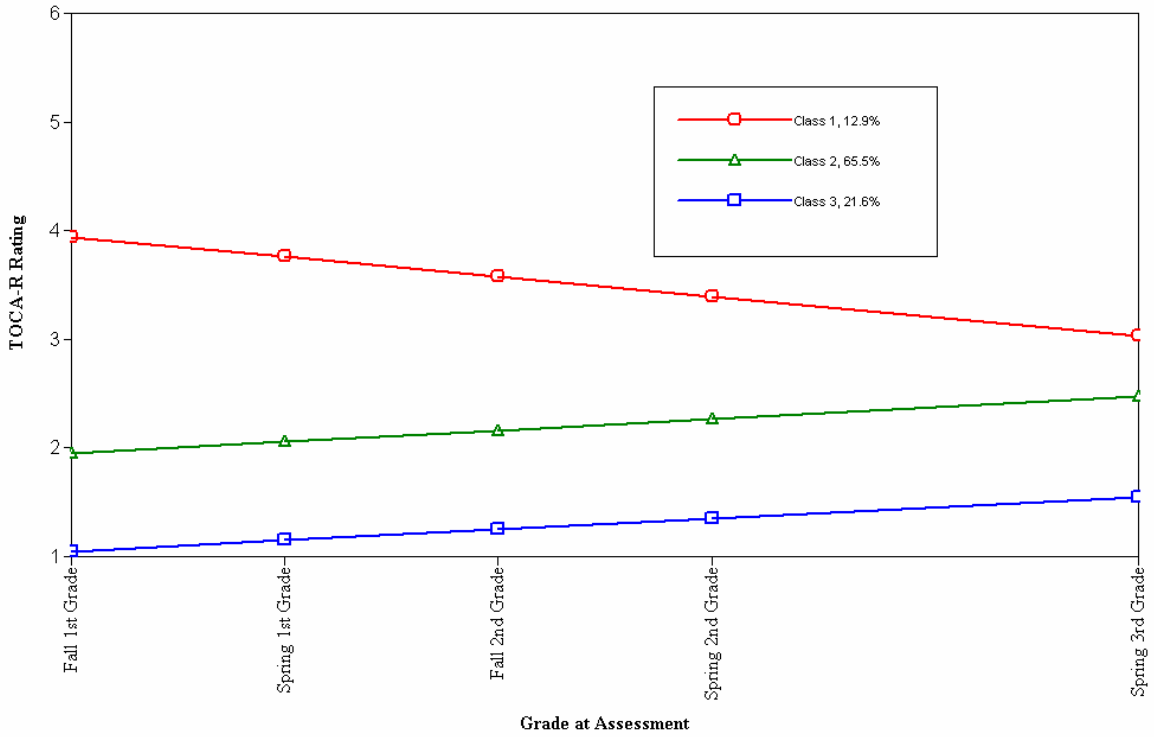
Table 5.3 Parameter Estimates for Boys' Final Three-Class Model

	Aggression Growth Estimates					
	High-Declining		***Moderate-Increasing***		***Low-Increasing***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.939	0.167*	1.951	0.072*	1.049	0.020*
α_1	-0.373	0.114*	0.211	0.041*	0.200	0.083*
$V(\zeta_0)$	0.241	0.031*	0.241	0.031*	0.005	0.002*
$V(\zeta_1)$	0.031	0.026	0.031	0.026	0.031	0.026
γ_{race}	0.359	0.425	0.956	0.284*	---	---
γ_{lunch}	0.861	0.512	0.146	0.324	---	---
γ_{age}	0.892	0.521	0.430	0.318	---	---
γ_{ready}	0.862	0.215*	0.437	0.181*	---	---
γ_{reject}	2.876	0.412*	1.921	0.376*	---	---
$V(\varepsilon_{1F})$	0.189	0.033*	0.189	0.033*	0.000	Fixed
$V(\varepsilon_{1S})$	0.324	0.038*	0.324	0.038*	0.019	0.011
$V(\varepsilon_{2F})$	0.686	0.107*	0.686	0.107*	0.430	0.089*
$V(\varepsilon_{2S})$	0.951	0.101*	0.951	0.101*	0.607	0.133*
$V(\varepsilon_{3S})$	0.994	0.192*	0.994	0.192*	0.232	0.228
$C(\varepsilon_{1F,} \varepsilon_{1S})$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$C(\varepsilon_{2F,} \varepsilon_{2S})$	0.465	0.102*	0.465	0.102*	0.465	0.102*
$C(\alpha_{0,} \alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	1.165	0.362*	0.802	0.142*	1.122	0.276*
τ_{rules}	-0.425	0.313	-0.390	0.134	-0.437	0.232
Class Prevalence	0.1294 (n=77)		0.6538 (n=390)		0.2167 (n=129)	

LL = -2717.331, df=37 BIC = 5671.16 Entropy = 0.88 BLRT = 0.000

* $p<0.05$

Figure 5.3 Boys' Trajectories of Aggressive Behavior



Patterns of Aggressive Behavior in Girls

The process of estimating the optimal growth model for girls parallels that for boys. The fit indices that inform model selection are reported in Table 5.4. For boys, the 3- and 4-class solutions were readily identified as the viable models for consideration. For girls, none of the models are strongly or consistently endorsed thus far. According to the BIC statistic, the 3-class solution is best; though the sample-size adjusted BIC continues to drop with each addition of a class. The continued improvement in SSABIC even when all other fit indices would reject a model suggests that it is not a reliable measure of fit in this case. The entropy statistic is acceptable for each of the models, and so is not helpful for differentiating

goodness-of-fit or explanatory power. Conversely, the ALRT rejects all but the 2-class solution.

Table 5.4 Fit Indices for Latent Class Solutions: Girls (n=581)

Base Models[a]							
Latent classes	LL	df	BIC	SSABIC	Entropy	ALRT	BLRT
2	-2468.173	23	5082.734	5009.718	0.906	0.0036	0.000
3	-2409.018	33	5028.074	4923.311	0.865	0.1762	0.000
4	-2366.317	43	5006.318	4869.809	0.846	0.1330	0.000
5	-2339.813	53	5016.958	4848.703	0.868	1.0000	0.000
6	-2305.446	63	5011.872	4811.871	0.823	0.5642	0.000
Modified Models							
3.1	-2061.292	39	4370.809	4246.999	0.908	0.020	0.000
3.2	-2061.456	38	4364.773	4244.137	0.908	0.014	0.000
4.1	-2021.872	49	4355.617	4200.061	0.848	0.098	0.000
4.2	-2021.991	48	4349.490	4197.108	0.847	0.256	0.000

[a] Base models free the parameters for the correlation of TOCA-R scores in Fall and Spring of 1st and 2nd grade, and the correlation of the growth factors (slope-intercept) is set to zero

Thus far, the 2-class solution is the best candidate for a final model. First, however, efforts are made to improve the fit of the 3- and 4-class solutions in order to provide a more rigorous comparison to the base 2-class model.

Modification indices for the girls' 3-class model paralleled those for boy's models in suggesting that the intercept and residual variances for the non-aggressive class should be allowed to vary from the other classes'. These parameters were freed in Model 3.1, with the results reported in Table 5.4. Estimation of this modified model notably improved model fit, but also resulted in a problematic parameter – a negative variance for the Class Three (non-aggressive) intercept. Because it was small and non-significant (β = -0.001, s.e.=0.002), the Class Three intercept variance was constrained to zero in the subsequent model. Results

of this modification are reflected in Model 3.2, which shows the same increased goodness-of-fit, now without any problematic estimates.

When the 4-class solution is modified, the same process unfolds. Model 4.1 for girls resulted in improved BIC and SSABIC, decreased – but still acceptable – entropy, and the ALRT is no longer acceptable. In addition, Model 4.1 estimates a negative variance for the intercept of Class Four (β = -0.001, s.e.=0.002). In Model 4.2 this parameter is set to zero, but again the ALRT indicates that this model does not provide a good description of the girls' data. The choice of the best model for girls, then, is between the base model 2-class solution and the modified 3-class solution (Model 3.2). The 3-class solution is unanimously endorsed and is therefore chosen as the best fitting model for girls. As was the case for boys, the best fitting model for girls identifies three distinct trajectories of aggressive behavior. Parameter estimates for the final girls' model are presented in Table 5.5. Figure 5.4 provides a graphical representation of these groups.

Eight percent (n=48) of the girls in the sample are most likely to be in Latent Class 1, which can be characterized as a High-Declining (HD) pattern of aggressive behavior. Like their male counterparts, these girls start at high levels of aggressive behavior in the Fall of first grade (α = 3.687, s.e. = 0.170) and consistently decrease in aggression through third grade (β = -0.418, s.e. = 0.107). The majority of girls in the sample are likely to be classified in Latent Class 2 (n=361, 62%), which describes a Moderate-Stable (MS) pattern of aggressive behavior. Girls in this class, on average, were rated 1.772 (s.e. = 0.046) on the TOCA-R scale in the Fall of first grade and showed no significant change at each subsequent assessment (β = 0.049, s.e. = 0.027). Finally, thirty percent of the girls in the sample (n=172) have the highest probability of membership in the Low-Stable (LS) trajectory. Girls in this

class are rated as non-aggressive by their teachers in the Fall of first grade ($\alpha = 1.058$, s.e.= 0.020), and at each assessment thereafter through third grade ($\beta = 0.067$, s.e. = 0.019)[10].

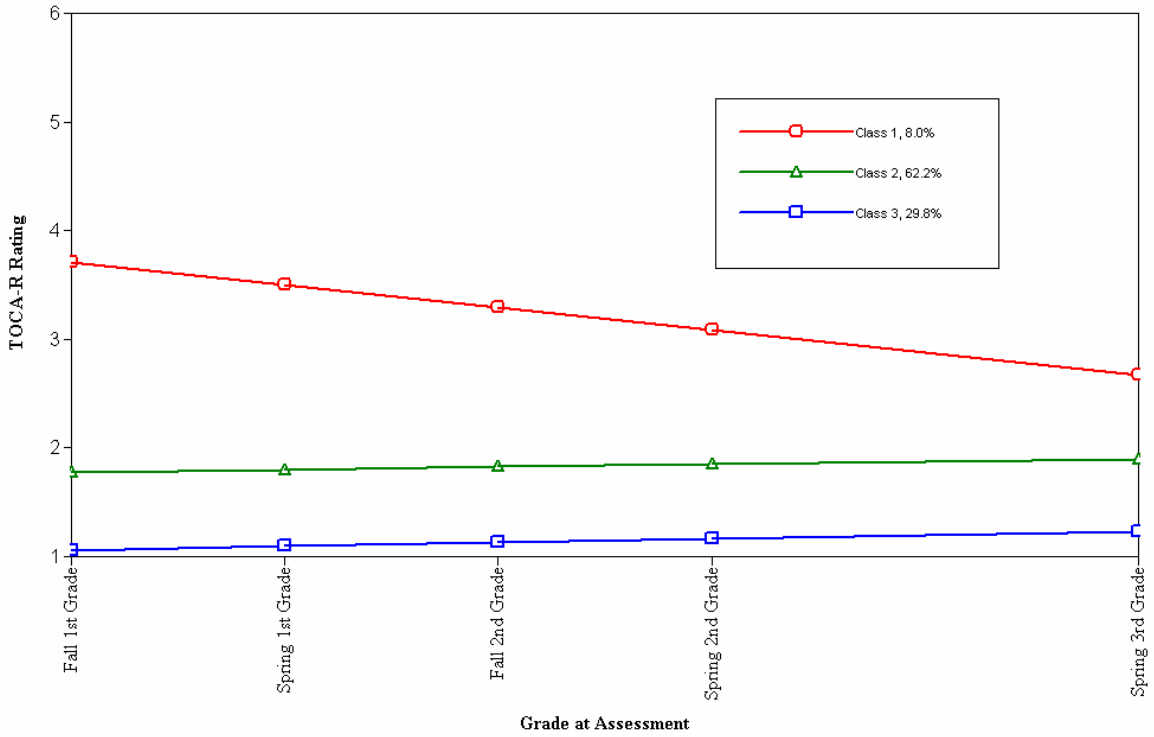
Table 5.5 Parameters Estimates for Three-Class Model: Girls (n=581)

	Aggression Growth Estimates					
	High-Declining		***Moderate-Stable***		***Low-Stable***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.687	0.170*	1.772	0.046*	1.058	0.020*
α_1	-0.418	0.107*	0.049	0.027	0.067	0.019*
$V(\zeta_0)$	0.130	0.023*	0.130	0.023*	0.000	Fixed
$V(\zeta_1)$	0.002	0.003	0.002	0.003	0.002	0.003
γ_{race}	1.126	0.736	0.363	0.277	---	---
γ_{lunch}	0.445	0.509	-0.142	0.239	---	---
γ_{age}	0.758	0.539	-0.242	0.238	---	---
γ_{ready}	0.891	0.211*	0.343	0.119*	---	---
γ_{reject}	1.976	0.361*	0.842	0.263*	---	---
$V(\varepsilon_{1F})$	0.213	0.033*	0.213	0.033*	0.007	0.004
$V(\varepsilon_{1S})$	0.262	0.038*	0.262	0.038*	0.013	0.004*
$V(\varepsilon_{2F})$	0.420	0.059*	0.420	0.059*	0.145	0.042*
$V(\varepsilon_{2S})$	0.414	0.041*	0.414	0.041*	0.284	0.069*
$V(\varepsilon_{3S})$	0.663	0.075*	0.663	0.075*	0.077	0.030*
$C(\varepsilon_{1F,} \varepsilon_{1S})$	0.006	0.003*	0.006	0.003*	0.006	0.003*
$C(\varepsilon_{2F,} \varepsilon_{2S})$	0.192	0.051*	0.192	0.051*	0.192	0.051*
$C(\alpha_{0,} \alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	0.383	0.408	1.885	0.184*	1.890	0.264*
τ_{rules}	-0.757	0.433	-0.073	0.122	-0.036	0.178
Class Prevalence	0.0829 (n=48)		0.6219 (n=361)		0.2952 (n=172)	
LL = -2061.456, df=38			BIC = 4364.77		Entropy = 0.908	

* $p<0.05$

[10] The slope estimate of 0.067 is significant at $p<.001$ but it is negligible in magnitude, hence the designation of this trajectory as low-stable, not low-increasing.

Figure 5.4 Girls' Patterns of Aggressive Behavior



The Influence of Covariates on Development of Aggression

Subsequent to the identification of the unique patterns of growth in aggression for boys and girls, I proceed to an examination of the extent to which risk factors differentiate the probability of class membership. Recall that the following covariates are included in the models: race, free lunch eligibility, age, school readiness, peer rejection, parental monitoring and parental rule setting. Regressing class membership on race, free lunch eligibility, age, school readiness and peer rejection captures the utility of these antecedent risk factors for predicting aggression trajectory membership. Parental monitoring

and rule-setting are established risk factors for aggression and are hypothesized to contemporaneously influence the development of aggressive behavior. However, these are retrospective measures assessed at the young adult interview and therefore likely reflect respondents' generalized recollections of their parents' styles over the duration of their childhood. As such, parental monitoring and rule-setting are not incorporated into the model in the same fashion as the prospective measures. Rather, the model uses these covariates in addition to the growth factors to define the trajectory classes. The most accurate characterization of the trajectory classes, then, is that they describe the patterns of aggressive behavior and the parenting experiences of the sample from first through third grade[11]. A limitation of this modeling approach is that these covariates cannot predict class membership, but because the predictive utility of these covariates is not subject to explicit testing, it is appropriate to include them in the model in the manner most consistent with their original measurement. For all covariates, odds ratios (OR) using the non-aggressive class as the reference group provide an intuitive measure of the influence of risk factors on the development of aggression from first through third grade.

Influence of Covariates on Class Membership for Boys

Table 5.6 summarizes the findings on the influence of covariates on the development of boys' aggression. The parameter estimates associated with each covariate are logit coefficients[12], and represent the expected change in the log odds of class membership

[11] For an economy of words, the identified trajectories are referred to as "aggression trajectories" or "patterns of aggressive behavior" throughout this document. The reader is reminded that in fact, the trajectories capture both patterns of aggressive behavior and the respondent's experience with their parents.
[12] Parameter estimates are also reported in Table 4.4 but are repeated here for ease of reference.

(relative to a reference category) associated with a one unit change in the covariate[13]. Inspection of the covariate parameter estimates and odds ratios (OR) reveals several things of note. Being nonwhite is significantly related to an increased risk of membership in the MI trajectory group relative to the LI group (OR = 2.60, CI=1.49-4.54), but does not place boys in the sample at higher risk of membership in the HD group. Eligibility for free or reduced *lunch* does not significantly predict membership in any of the three classes, nor does a dichotomous measure of *age.*

Among the antecedent risk factors included in the model, school readiness and peer rejection appear to have the most powerful influence on class membership. Recall that each of these covariates is measured on a scale of one to six, with higher scores corresponding to higher levels of risk. From Table 5.6 we see that boys who are one unit above the mean score[14] for school readiness have significantly increased odds of membership in either the MI group (OR=1.55, CI=1.09-2.21) or the HD group (OR=2.37, CI=1.55-3.61). The relationship of peer rejection to aggressive trajectory membership is even more striking. Boys who are rejected by their peers experience notably higher risk than their accepted counterparts of membership in the MI trajectory relative to the LI trajectory (OR=6.83, CI=3.26-14.27), and even more pronounced risk for membership in the HD trajectory (OR=17.74, CI=7.92-39.77). Conversely then, boys who are deemed by their teachers to be more prepared for schooling than their peers, and who are accepted by their peers, have significantly decreased risk of membership in either of the aggressive groups.

[13] The measurement portion of the growth mixture model is given by: $y_{it} = \eta_{0i} + \eta_{1i} a_t + \varepsilon_{it}$, where $a_t = 0, 0.5, 1.0, 1.5, 1.5$. The structural component is given by: $\eta_{0i} = \alpha_{0k} + \gamma_{0k} x_i + \zeta_{0i}$; $\eta_{1i} = \alpha_{1k} + \gamma_{1k} x_i + \zeta_{1i}$, where x_i = race, lunch, age, ready, reject. The probability of membership in a given class given some value on a covariate is calculated with: $P(c=k|x) = \exp(\alpha_k + \gamma_k x) / \Sigma [\exp(\alpha_k + \gamma_k x)$.

[14] The measures for *Ready* and *Reject* were mean-centered for ease of interpretation.

Table 5.6 Association of Trajectory Class Membership with Covariates: Boys (n=597)

Antecedent covariates predicting class membership

Covariate	Class	Est (SE)	OR	CI
Race	HD	0.359 (0.524)	1.432	0.513-4.00
	MI	0.956 (0.284)*	2.601*	1.49-4.54
	LI	---	---	---
Lunch	HD	0.861 (0.512)	2.366	0.867-6.46
	MI	0.146 (0.324)	1.157	0.613-2.19
	LI	---	---	---
Age	HD	0.893 (0.521)	2.440	0.879-6.79
	MI	0.430 (0.318)	1.537	0.824-2.87
	LI	---	---	---
Ready	HD	0.862 (0.215)*	2.368*	1.55-3.61
	MI	0.437(0.181)*	1.548*	1.09-2.21
	LI	---	---	---
Reject	HD	2.876 (0.412)*	17.74*	7.92-39.77
	MI	1.921 (0.376)*	6.828*	3.26-14.27
	LI	---	---	---
Intercept	HD	-1.513 (0.630)*	0.220*	0.064-0.758
	MI	1.138 (0.469)*	3.121*	1.24-7.83
	LI	---	---	---

Covariates used to define trajectory classes:

		Threshold (SE)	OR	CI	P(x=1)[a]
Monitor	HD	1.165 (0.362)*	0.958	0.396-2.314	0.238
	MI	0.802 (0.142)*	1.377	0.731-2.597	0.310
	LI	1.122 (0.276)*	---	---	0.246
Rules	HD	-0.425 (0.313)	0.988	0.462-2.113	0.605
	MI	-0.390 (0.134)*	0.955	0.553-1.648	0.596
	LI	-0.437 (0.232)	---	---	0.607

[a] $P(\text{covariate}=1|c) = 1/1+\exp^{\tau}$

* $p<0.05$

To understand the effects of the covariates as a whole, it is helpful to calculate the predicted probabilities of class membership based on the estimated model for various combinations of values on the covariates. Table 5.7 summarizes several predicted probabilities based on various combinations of the covariates *Ready* and *Reject* when all other covariates are held at their zero. The predicted probabilities highlight the difference between

a boy in the sample who is above the mean on both *Ready* and *Reject* (and therefore at increased risk) with a probability of HD membership of 0.225 compared with a boy who is below risk on both covariates and a probability of HD membership of 0.004.

Table 5.7 Boys' Predicted Probability of Class Membership Based on Covariates

Value of Covariate		Predicted Probability of Class Membership		
Ready	*Reject*	HD	MI	LI
0	0	0.051	0.719	0.23
0	+1 sd	0.142	0.816	0.043
+1 sd	0	0.093	0.766	0.140
+1 sd	+1 sd	0.225	0.753	0.023
0	-1 sd	0.001	0.335	0.655
-1 sd	0	0.026	0.624	0.350
-1 sd	-1 sd	0.004	0.225	0.771

Note: all other covariates held at zero

Neither of the retrospective measures of covariates, *Monitor* or *Rules*, appears to be particularly helpful in delineating class membership. The confidence intervals for each of the odds ratios contain the value 1.0, which means that the odds of class membership in either HD or MI are not significantly different from the odds of membership in the LI trajectory, regardless of risk on either covariate. The non-significant relationship is further observed in the predicted probabilities for each class. For example, among boys in the HD class, 23.8 percent are predicted to have reported low levels of parental monitoring while growing up. For the MI and LI groups, the predicted probabilities are 31 percent and 24.6 percent, respectively. With respect to parental rule setting, 60.5 percent of the HD class is predicted to have reported little rule setting, with 59.6 percent of the MI class and 60.7 percent of the LI class predicted to report the same. These probabilities are largely similar across classes, and

thus it appears that the measures of parental monitoring and supervision are not particularly powerful for distinguishing class membership for boys.

An unexpected finding is that the proxy measure for socioeconomic status, *free lunch status*, does not significantly distinguish class membership for any of the groups. This result may be a statistical artifact stemming from the collinearity of race and socioeconomic status in these data. Estimating two additional models, first including only *race* and then only *free lunch status*, supports this hypothesis. Both models yield the equivalent substantive results as the full model. Complete results for each of these models are reported in Appendix B.

Influence of Covariates on Class Membership for Girls

The influence of covariates on class membership for girls is summarized in Table 5.8. *Race* is not significantly related to an increased risk of membership in either the HD or the MS trajectory relative to the LS trajectory. As was the case for boys, eligibility for free or reduced *lunch* and *age* still do not significantly predict or differentiate membership in any of the three classes. Indeed, school readiness and peer rejection are the only antecedent risk factors that have significant influence on class membership for girls. Girls assessed by their teachers at higher risk than their peers have significantly increased odds of membership in either the MS group (OR=1.409, CI=1.12-1.79) or the HD group (OR=2.438, CI=1.61-3.69).

Table 5.8 Association of Trajectory Class Membership with Covariates: Girls (n=581)

Antecedent covariates predicting class membership

Covariate	Class	Est (SE)	OR	CI
Race	HD	1.126 (0.736)	3.083	0.729-13.05
	MS	0.363 (0.277)	1.438	0.835-2.47
	LS	---	---	---
Lunch	HD	0.445 (0.509)	1.560	0.576-4.23
	MS	-0.142 (0.239)	0.868	0.544-1.39
	LS	---	---	---
Age	HD	0.758 (0.539)	2.134	0.742-6.14
	MS	-0.242 (0.238)	0.785	0.493-1.25
	LS	---	---	---
Ready	HD	0.891 (0.211)*	2.438*	1.61-3.69
	MS	0.343 (0.119)*	1.409*	1.12-1.79
	LS	---	---	---
Reject	HD	1.976 (0.361)*	7.214*	3.55-14.64
	MS	0.842 (0.263)*	2.321*	1.38-3.89
	LS	---	---	---
Intercept	HD	-3.718 (1.065)*	0.024*	0.003-0.196
	MS	1.001 (0.292)*	2.721*	1.54-4.84
	LS	---	---	---

Covariates used to define trajectory classes:

		Threshold (SE)	OR	CI	P(x=1)[a]
Monitor	HD	0.383 (0.408)	4.512	1.75-11.63*	0.405
	MS	1.885 (0.184)*	2.055	0.824-5.13	0.132
	LS	1.890 (0.264)*	---	---	0.131
Rules	HD	-0.757 (0.433)	1.005	0.526-1.92	0.681
	MS	-0.073 (0.122)	1.037	0.669-1.61	0.518
	LS	-0.036 (0.178)	---	---	0.509

[a] $P(\text{covariate}=1|c) = 1/1+\exp^{\tau}$

* $p<0.05$

Girls who are rejected by their peers are at increased risk for membership in the MS trajectory relative to the LS trajectory by a factor of 2.32 (CI=1.38-3.89), and their risk for membership in the HD class increases by a factor of 7.214 (CI=3.55-14.64). While not as

remarkable as the boys' increased risk (OR_{Boys}=17.74), peer rejection still appears to exert powerful influence on the aggression trajectories of these girls.

Table 5.9 summarizes the predicted probabilities of class membership in each class for various combinations of values for *Ready* and *Reject*, with all other covariates held at zero. The girls who are most likely to exhibit a pattern of behavior consistent with the LS trajectory are below the average risk with respect to school readiness and peer rejection (Pr=0.717). These girls also have a near zero probability of being assigned to the HD trajectory class. The retrospectively measured covariates, *Monitor* and *Rules*, show a different relationship with class membership for girls than was observed for boys.

Table 5.9 Girls' Predicted Probability of Class Membership Based on Covariates

Value of Covariate		Predicted Probability of Class Membership		
Ready	*Reject*	HD	MS	LS
0	0	0.006	0.727	0.267
0	+1 sd	.001	0.916	0.074
+1 sd	0	0.014	0.794	0.192
+1 sd	+1 sd	0.021	0.929	0.049
0	-1 sd	0.003	0.373	0.625
-1 sd	0	0.003	0.641	0.357
-1 sd	-1 sd	0.0007	0.282	0.717

Note: all other covariates held at zero

Whereas for boys, neither has a significant relationship with class membership, *Monitor* evinces a significant relationship with membership in the HD group relative to the LS group (OR 4.51, CI=1.75-11.63). This means that girls who report lower levels of parental monitoring are at increased risk for membership in the HD class relative to the LS group. The relationship for girls in the MS group is consistent with the expectation of lower

levels of parental monitoring increasing risk for aggressive behavior patterns (OR=2.055), but this relationship is not significant (CI=0.824-5.13). When the threshold parameters are used to calculate predicted probabilities, we see that 40.5 percent of the girls in the HD group are likely to have reported low parental monitoring, compared with 13.2 percent of the MS girls and 13.1 percent of the girls in the LS trajectory. The influence of *Rules* on class membership is not significant for any group.

The proxy measure for socioeconomic status, *free lunch status*, does not significantly distinguish class membership for girls. Again, this finding is unexpected in light of the existing empirical research establishing SES as predictive of class membership. Two additional models (one including only *race* and a second with *lunch* only) are presented in Appendix B, and support the hypothesis that this finding is a reflection of the collinearity of race and socioeconomic status in these data. Both models yield the equivalent substantive results as the full model.

Relationship of Trajectory Classes to Distal Outcomes

The presentation of findings turns now to the question of whether knowledge of aggression trajectory membership is helpful for understanding the adolescent offending outcomes these students experience. The utility of a dynamic measure of aggression as an independent variable for predicting to distal outcomes is assessed by regressing four measures of distal outcomes on class membership.

The Relationship Between the Development of Aggression and Boys' Juvenile Offending

Results of the analyses on distal outcomes for boys are summarized in Table 5.10. The first adolescent outcome of interest is simply whether boys in the data experienced at least one arrest between the ages of ten and eighteen. Among all the boys in the sample, 27 percent (n=161) were arrested at least one time. A dichotomous measure of arrest is regressed on class membership to assess the probability of arrest specific to each class. Results show that class membership significantly differentiates the likelihood of arrest for all classes. The odds of arrest for boys in the HD trajectory are 3.456 those for boys in the LI group (CI=1.416-8.431), and boys in the MI group are also at significantly increased risk of arrest compared to boys in the LI group (OR=2.490, CI=1.176-5.272). Roughly thirty-six percent of HD boys are expected to experience at least one arrest, compared with 29.2 percent of boys in the MI group and 14.2 percent of boys in the LI group.

Knowledge of aggression trajectory membership also has a significant relationship with the dichotomous measure of violent offending. Of the 597 boys in the sample, 22.3 percent (n=133) were arrested for a violent offense. This probability varies significantly, however, according to which trajectory a boy's aggressive behavior most resembled. Boys in the HD trajectory had 3.815 (CI=1.508-9.650) the odds of a violent arrest than their LI counterparts, and a predicted probability of violent arrest of 0.304. Membership in the MI trajectory also distinguished boys with higher risk of violent arrest (OR=2.854, CI=1.360-5.990).

Table 5.10 Association of Boys' Trajectory Class Membership with Distal Outcomes

	Trajectory Class	Proportion with Outcome[a]	OR	95% CI
Any Official Arrest	HD	0.364	3.456*	1.416-8.431
	MI	0.292	2.490*	1.176-5.272
	LI	0.142	--	--
Any Violent Arrest	HD	0.304	3.815*	1.508-9.650
	MI	0.247	2.854*	1.360-5.990
	LI	0.103	--	--
Categorical Offending Mix				
Violent only	HD	0.093	0.337	0.084-1.352
	MI	0.078	0.409	0.121-1.387
	LI	0.033	--	--
Violent and Non-violent	HD	0.212	0.260*	0.102-0.666
	MI	0.168	0.351*	0.165-0.744
	LI	0.069	--	--
Non-violent only	HD	0.059	0.299*	0.112-0.799
	MI	0.045	0.418	0.174-1.008
	LI	0.044	--	--
No offending	HD	0.635	--	--
	MI	0.709	--	--
	LI	0.853	--	--

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{\tau}$
Note: OR = odds ratio; CI = 95% confidence interval
*$p<0.05$

The final distal outcome summarized in Table 5.10 examines the relationship between aggression trajectory membership and a categorical measure of offending mix. This measure includes four mutually exclusive categories to represent those whose offense mix comprised: 1)violent offending only, 2) a mix of violent and non-violent offenses, 3) non-violent offenses only, and 4) no offending at all. The observed distribution of this variable in the data is as follows: violent offending only = 0.07, violent and non-violent offending = 0.152, non-violent offending only = 0.047, and no offending = 0.730.

Note first that the predicted probabilities for the No Offending category are the complements of the predicted probabilities of the dichotomous measure of arrest. Second, while the predicted probabilities for each trajectory are consistent with expectations (i.e. the HD trajectory has the highest probability of violent offending only), the relationships between aggression trajectory and offense mix are less robust than those observed for the dichotomous measures of offending and violent offending. Boys in the HD trajectory are less likely to commit a mix of offenses (OR=0.260, CI=0.102-0.666) or non-violent offenses only (OR=0.299, CI=0.112-0.799) and boys in the MI trajectory have lower odds of committing a mix of violent and nonviolent offenses (OR=0.351, 0.165-0.744).

The Relationship Between Development of Aggression and Girls' Juvenile Offending

The analyses were repeated for the girls in the sample, and results are reported in Table 5.11. To begin, the consistent empirical observation that plagues prediction efforts for girls – that they offend at lower rates than boys – is reproduced in these data. Of the 581 girls in the sample, 11.7 percent (n=68) have official arrest records from ages 10 through 18. Nevertheless, when the dichotomous measure of arrest is regressed on class membership, results show a significant relationship for girls in the HD class. These girls are roughly 7.5 times more likely (CI=3.034-18.30) their non-aggressive peers to experience an arrest during adolescence. Membership in the MS trajectory group does not appear to place girls at increased risk for arrest (OR=1.445, CI=0.703-2.970).

Table 5.11 Association of Girls' Trajectory Class Membership with Distal Outcomes

	Trajectory Class	Proportion with Outcome[a]	OR	95% CI
Any Official Arrest	HD	0.373	7.452*	3.034-18.300
	MS	0.103	1.445	0.703 – 2.970
	LS	0.074	---	---
Any Violent Arrest	HD	0.293	6.068*	2.315-15.904
	MS	0.064	1.00	0.450-2.224
	LS	0.064	---	---
Categorical Offending Mix				
Violent only	HD	0.143	0.256*	0.076-0.867
	MS	0.045	0.918	0.341-2.468
	LS	0.041	--	--
Violent and Non-violent	HD	0.146	0.170*	0.064-0.450
	MS	0.019	1.016	0.453-2.278
	LS	0.024	--	--
Non-violent only	HD	0.078	0.129*	0.049-0.335
	MS	0.042	0.631	0.272-1.462
	LS	0.005	--	--
No offending	HD	0.633	--	--
	MS	0.894	--	--
	LS	0.930	--	--

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{\tau}$
Note: OR = odds ratio; CI = 95% confidence interval
*$p<0.05$

The model for a dichotomous measure of violent offending produces similar results. In the overall sample of girls, 8.3 percent (n=48) were arrested for a violent offense. When a dynamic measure of aggression is utilized, girls in the HD group are significantly and strongly distinguished from girls in the LS class (OR=6.068, CI=2.315-15.904). Girls in the MS trajectory appear to be indistinguishable from the LS girls with respect to violent offending. The predicted probability of violent offending is equal for the two classes (Pr=0.064) and the odds ratio of 1.0 confirms that the odds of a violent arrest are equivalent for the MS and LS trajectories.

The observed distribution of offense mix for girls in the sample is as follows: 1) violent offending only = 0.052, 2) mix of violent and non-violent offending = 0.031, 3) non-violent offending only = 0.034, and 4) no offending = 0.883. When this categorical measure is included as a distal outcome influenced by aggression trajectory membership, only the HD group is distinguished as significantly related to the offense mix categories. Girls in the HD aggression trajectory have a predicted probability = 0.143 and 0.145 of violent offending only or violent and non-violent offending, respectively. As was the case for boys, membership in the MS group does not differentiate risk for these categories relative to the LS group.

Aggression Trajectory Membership and Age of Onset for Boys

The next stage of the analyses examines the effects of aggression trajectory membership and the age of onset of criminal behavior as measured by arrest. Dummy variables for onset at each age from ten through sixteen were regressed on aggression trajectory class membership. Ages seventeen and eighteen were collapsed into one dummy variable capturing onset at either age. The results (see Table 5.12) reveal no significant relationships among patterns of aggression during elementary school and the age of onset of criminal behavior. Because onset is a relatively rare event, particularly when measured by official arrest data, and because here the occurrence of onset is distributed over eight time periods, it is likely the case that there is insufficient variation in each dummy category to detect significant relationships. To assess this possibility, the analysis was rerun on a dichotomized measure of age of onset. Onset before age fifteen was selected as the demarcation point because roughly half (n=85) of all the offenders in the boys' sample experienced onset of official offending behavior before then.

Estimation of this model (See *Modified Model* panel in Table 5.12) suggests that aggression trajectory membership does have a meaningful influence on age of onset, but this relationship was masked in the first analysis.

Table 5.12 Association of Boys' Trajectory Class Membership with Age of Onset

Onset at age:	Trajectory Class	Percentage with Outcome[a]	HOR	95% CI
10	HD	0.000	0.000	0.000-0.000
	MI	0.003	0.356	0.021-6.184
	LI	0.007	---	---
11	HD	0.019	62648	***
	MI	0.009	30801	***
	LI	0.000	---	---
12	HD	0.028	4.324	0.187-99.86
	MI	0.011	1.610	0.084-30.89
	LI	0.007	---	---
13	HD	0.094	1.974	0.432-9.025
	MI	0.069	1.407	0.454-4.359
	LI	0.050	---	---
14	HD	0.094	***	***
	MI	0.071	***	***
	LI	0.000	---	---
15	HD	0.053	3.521	0.483-25.69
	MI	0.056	3.722	0.694-19.947
	LI	0.016	---	---
16	HD	0.015	0.283	0.019-4.288
	MI	0.072	1.460	0.442-4.826
	LI	0.051	---	---
17-18	HD	0.033	1.087	0.154-7.684
	MI	0.016	0.523	0.100-2.744
	LI	0.031	---	---
Modified Model				
Before age 15	HD	0.212	3.979*	1.324-11.957
	MI	0.156	2.734*	1.114-6.710
	LI	0.063	---	---

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{logit}$

Note: HOR = hazard odds ratio; CI = confidence interval

*$p<0.05$

Boys who were on the HD trajectory of aggressive behavior during elementary school are almost four times more likely than boys from the LI group to experience onset before age fifteen (HOR=3.979, CI=1.324-11.957). Membership in the MI trajectory membership also puts boys at increased risk of onset before age 15 (HOR=2.734, CI=1.114-6.710).

Aggression Trajectory Membership and Age of Onset for Girls

The same analysis of age of onset as a distal outcome for girls (see Table 5.13) yields similar results as for boys, with the exception of two significant findings. Girls in the HD trajectory have significantly increased risk of experiencing onset at age thirteen (HOR=14.455, CI=2.697-77.471) and age fifteen (OR=18.504, CI=1.194-286.699). These significant relationships do not appear to be part of a larger, systematic pattern, and examination of the predicted probabilities reveals that for every age until seventeen, girls in the HD trajectory group are at higher risk of onset. This result is not surprising, nor is it particularly informative. The modified model with a dichotomized measure of onset is therefore estimated for girls. Age fourteen was selected as the cut point for the girls' model, as the 32 girls who experienced onset before age fourteen comprise almost half (47.1 percent) of all girls who committed any offense. Results of the re-estimated model are reported in the lower panel of Table 5.13. A clear relationship between membership in the HD trajectory and an increased probability of experiencing onset before age fourteen (HOR=9.458, CI=3.022-29.600) is now evident. Membership in the MS group is not associated with increased risk of onset before age fourteen relative to the LS group.

Table 5.13 Association of Girls' Trajectory Class Membership with Age of Onset

Onset at age:	Trajectory Class	Percentage with Outcome[a]	HOR	95% CI
10	HD	0.021	70931	***
	MS	0.000	1.000	1.000-1.000
	LS	0.000	---	---
11	HD	0.022	4.616	0.141-150.927
	MS	0.003	0.682	0.010-45.605
	LS	0.005	---	---
12	HD	0.070	4.313	0.721-25.783
	MS	0.014	0.804	0.165-3.920
	LS	0.017	---	---
13	HD	0.146	14.455*	2.697-77.471
	MS	0.022	1.942	0.392-9.632
	LS	0.012	---	---
14	HD	0.042	2.072	0.213-20.190
	MS	0.020	0.971	0.188-5.020
	LS	0.021	---	---
15	HD	0.087	18.504*	1.194-286.699
	MS	0.015	3.020	0.206-44.240
	LS	0.005	---	---
16	HD	0.036	3.053	0.260-35.90
	MS	0.012	0.973	0.162-5.852
	LS	0.012	---	---
17-18	HD	0.000	0.000	0.000-0.000
	MS	0.009	1.507	0.145-15.654
	LS	0.006	---	---
Modified Model				
Before age 14	HD	0.245	9.458*	3.022-29.600
	MS	0.040	1.211	0.413-3.552
	LS	0.033	---	

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{logit}$

Note: HOR = hazard odds ratio; CI = confidence interval

*$p<0.05$

Linking Boys' Childhood Aggression with Juvenile Offending and Adult Offending

The final question of how the development of aggression during childhood influences adult offending, and desistance from adult offending in particular, can now be examined. To begin, I estimate a model that treats adult offending just as any other dichotomous outcome linked with the GMM. These results are reported as Model 1 in Table 5.14. The significant relationship of childhood aggression trajectories with later offending is maintained in this model. Boys in the HD class are almost seven times more likely than their non-aggressive peers to experience adult incarceration, and boys in the MI trajectory are almost five time as likely. However, while this model provides an good initial indication of a positive association between childhood development and adult outcomes, it does not take behavior in the intervening developmental period into account, and is therefore not consistent with the conceptual model linking childhood development to adulthood behavior through adolescent development and behavior. A second model more consistent with this pathway is estimated. Model 2 includes consideration of juvenile offending by specifying a two-part growth model. The growth model for aggression remains the same, but juvenile offending is now also measured as a growth model with two known classes – those who committed a juvenile offense and those who did not. This allows the childhood growth model to influence the juvenile growth model, which in turn is related to the adult offending (measured by adult incarceration). This model shows that of those who committed a juvenile offense, 39.8 percent go on to experience adult incarceration, compared with 7.6 percent of those who did not experience arrest as a juvenile. Estimation of two-part models does not generate transitional odds ratios for the entire two-part growth process.

Table 5.14 Association of Boys' Trajectory Class Membership with Adult Incarceration

	Trajectory Class	Proportion with Outcome[a]	OR	95% CI
Adult Incarceration Model 1	HD	0.246	6.891*	1.580-30.050
	MI	0.183	4.710*	1.134-19.571
	LI	0.045	---	---

	Childhood Trajectory Class	Adolescent Outcome	Adult Outcome	Class Count
Model 2	HD	JA	AI	14
	(n=77)	JA	NI	15
		NJ	AI	5
		NJ	NA	43
	MI	JA	AI	48
	(n=398)	JA	NI	68
		NJ	AI	25
		NJ	NA	257
	LI	JA	AI	3
	(n=122)	JA	NI	14
		NJ	AI	3
		NJ	NA	102

Class Transition Probabilities: Childhood to Adolescence	JA	NJ
HD	0.709	0.635
MI	0.860	0.709
LI	0.140	0.860

Class Transition Probabilities: Adolescence to Adulthood	AI	NA
JA	0.398	0.602
NJ	0.076	0.924

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{\tau}$

Note: OR = odds ratio; CI = 95% confidence interval

*$p<0.05$

Therefore, to show the various progressions of behavior over the three phases of development, the second panel of Table 5.14 reports the latent class counts for each possible pattern based on the estimated model. For example, of the 77 boys in the HD trajectory class, 14 then also experience both juvenile arrest (JA) and adult incarceration (AI). Forty-three of the boys in the HD class during childhood were not arrested as juveniles (NJ), nor were they incarcerated as adults (NA). These patterns are particularly helpful for distinguishing highly stable patterns of behavior over time from those that suggest changing behavior, potentially toward desistance. One such group of interest is made up of the fifteen boys who were in the HD trajectory during elementary school, experienced arrest as juveniles, but have not experienced adult incarceration.

Linking Girls' Childhood Aggression with Juvenile Offending and Adult Offending

Girls' aggression trajectory membership is not as strongly related to adult offending as it is for boys. The odds ratios reported in the first panel of Table 5.15 suggests that membership in any of the three groups does not significantly differentiate the likelihood of experiencing incarceration as an adult. Consideration of the percentage of girls expected to actually experience adult offending reveals one possible explanation for this. Even among the most aggressive group of girls, only two percent are expected to experience adult incarceration. One percent of the MS girls and just over half a percent of LS girls are expected to be incarcerated as adults. This finding, or lack thereof, echoes findings observed in much of the literature on female involvement in offending. There is simply not enough variation in the outcome to detect any relationship with potential antecedents.

Table 5.15 Association of Girls' Trajectory Class Membership with Adult Incarceration

	Trajectory Class	Proportion with Outcome[a]	OR	95% CI
Adult Incarceration Model 1	HD	0.022	3.805	0.221-65.402
	MS	0.011	1.939	0.207-18.159
	LS	0.006	---	---

	Childhood Trajectory Class	Adolescent Outcome	Adult Outcome	Class Count
Model 2	HD	JA	AI	1
	(n=47)	JA	NI	16
		NJ	AI	0
		NJ	NA	30
	MS	JA	AI	1
	(n=361)	JA	NI	37
		NJ	AI	3
		NJ	NA	320
	LS	JA	AI	0
	(n=173)	JA	NI	13
		NJ	AI	1
		NJ	NA	159

Class Transition Probabilities: Childhood to Adolescence	JA	NJ
HD	0.356	0.644
MS	0.105	0.895
LS	0.076	0.924

Class Transition Probabilities: Adolescence to Adulthood	AI	NA
JA	0.029	0.971
NJ	0.008	0.992

[a] Percentages are based on threshold estimates and are given by: $P(y=1|c) = 1/1+\exp^{\tau}$

Note: OR = odds ratio; CI = 95% confidence interval

*p<0.05

Results from Model 2, which was specified to be consistent with the conceptual model, are somewhat more informative. The addition of adult offending outcomes does little to distinguish these results from those for the analyses of the relationship between childhood aggression and juvenile offending. That is, the model confirms that HD girls are more likely than their peers to be involved in juvenile offending. This model is notably distinguished from the previous models, however, in that the modal behavioral trend observed in all groups is one of non-offending.

Summary of Findings

Patterns of Aggressive Behavior Identified for Boys and Girls

Application of General Growth Mixture Modeling to the Baltimore Prevention Project data yielded a 3-class solution as the best model to describe patterns of aggressive behavior from first to third grade for boys and girls separately. The model for boys shows a High-Declining (HD) pattern of behavior beginning with high levels of aggression in the Fall of first grade and steadily declining thereafter. This trajectory group approximates the behavior of about thirteen percent of the 597 boys in the sample. Most of the boys in the sample (roughly 65 percent) exhibit behavior consistent with the second trajectory, termed Moderate-Increasing (MI). This group of boys began the first grade already exhibiting low to moderate levels of aggression, and teachers reported increased aggression at each assessment period after the Fall of first grade. On average, boys in the MI group were assessed at a 1.951 on the TOCA-R scale, and by the Spring of third grade their average TOCA-R score was 2.48.

Finally, a third trajectory describes the behavior of boys who, at first grade entry, did not exhibit any aggressive behavior. TOCA-R scores for these boys did increase over time, so that the average TOCA-R assessment in Spring of third grade was 1.59. This trajectory was labeled Low-Increasing (LI) to reflect the statistically significant estimate for the slope growth parameter. However, the increase over time is marginal, and in light of the low initial status, boys in the LI trajectory are functionally a non-aggressive group. They account for about 22 percent of boys in the sample.

The best model to describe patterns of girls' aggressive behavior in elementary school is also a 3-class solution, which bears more similarity than difference to the boys model. As was observed for boys, one trajectory identifies a small group of girls – just over eight percent – who initially exhibit high levels of aggression but desist in their aggressive behavior over time. This group of girls, also labeled High-Declining (HD) moves from an average TOCA-R score of 3.687 at first grade entry to an average score of 2.642 in the Spring of third grade. The largest group of girls (62 percent) is most likely to behave in accordance with the second identified trajectory, the Moderate Stable (MS) group. Girls in this trajectory begin first grade with moderate levels of aggression (the average TOCA-R score is 1.772), and longitudinal assessments of their behavior reveal no significant change. Finally, the third trajectory identified for girls represents about thirty percent of the sample and characterizes a Low-Stable pattern of behavior. These girls are non-aggressive at the beginning of first grade as reflected by the average TOCA-R score of 1.058, and are non-aggressive at the end of third grade, when the average TOCA-R score is 1.23. Although the slope growth parameter for this group is positive and significant, it is sufficiently small in magnitude to warrant the label Low-Stable (LS).

Relationships Among Risk Factors and Trajectory Membership

Analyses did not reveal significant relationships between the covariates *lunch, age, monitor* or *rules* and membership in any of the three trajectories identified for boys. *Race* evinced a significant relationship with the MI group only, suggesting that being Nonwhite increases one's odds of membership in that group relative to the LI group of boys. *Ready* and *Reject* were both strongly associated with the MI and the HD trajectory groups. Higher levels of risk on either of these covariates were associated with increased probability of membership in the MI and HD groups relative to the LI group.

For girls, only *Ready, Reject,* and *Monitoring* were found to be significantly associated with trajectory membership. Higher levels of risk on the covariates *Ready* and *Reject* predict membership in the HD and the MS groups. With respect to parental monitoring, girls in the HD trajectory were more likely to have recollected low levels of monitoring than girls in the other classes.

Aggression Trajectory Membership and Distal Outcomes

Aggression trajectory membership for boys significantly differentiated the probability of two dichotomous measure of later offending: any offending and violent offending. Boys in the HD trajectory have a predicted probability of offending of 0.364 –significantly higher than the predicted probability for MI boys of 0.292, which in turn is significantly different than the expectation for LI boys, who have a 0.142 probability of offending. Violent offending is similarly differentiated for boys based on trajectory membership, with probabilities of 0.304, 0.247 and 0.103 for the HD, MI and LI groups respectively. Results

for the categorical offending mix variable are less clear and it appears that offending trajectories do not systematically distinguish the categories captured with this variable.

Trajectory membership for girls is also associated with differing arrest outcomes, though only one pattern of aggressive behavior in elementary school, the High-Declining pattern, significantly differentiates girls at higher risk for offending behavior. Girls in the HD group have a predicted probability of offending of 0.373 compared with 0.103 and 0.074 for the MS and LS girls. HD girls are more than six times as likely as other girls in the sample to commit a violent offense. The categorical offense mix measure for girls, like that for boys, does not provide additional insight into the impact of trajectory membership on juvenile offending outcomes.

Aggression Trajectory Membership and Age of Onset

The initial analysis for age of onset did not reveal a systematic relationship between aggression trajectory membership and specific ages of onset for boys. Subsequent analysis of age of onset before age fifteen detected some notable relationships. Namely, membership in the HD trajectory increases the risk of onset before age fifteen by a factor of almost four, and membership in the MI trajectory group increases this risk by a factor of almost three.

Similarly, analysis of specific ages of onset for girls did not illuminate the predictive influence of the three trajectory groups. When onset before age fourteen was compared with onset at age fourteen or thereafter, however, girls in the HD trajectory emerged as more than nine times as likely to experience onset before age fourteen. Risk of onset before age fourteen was not significantly different for girls in the MS trajectory relative to their non-aggressive peers.

Linking Development From Childhood to Adulthood

Findings on the relationship between early childhood aggression, juvenile offending and adult offending are quite dissimilar for boys and girls, particularly with respect to indications of desistance. While various patterns emerged for boys, some of which are suggestive of a desistance process, virtually no girls experienced adult incarceration. However, rather than suggesting that girls' early development does not explain variation in later behavior, this result is consistent with existing research that shows earlier desistance for girls compared to boys. This is taken as cause for continued attention to girls' development rather than cause to abandon interest in it.

CHAPTER SIX: DISCUSSION AND CONCLUSIONS

Patterns of Aggressive Behavior in Elementary School

The identification of three distinct patterns of aggressive behavior during elementary school for boys is consistent with existing research, which has generally identified three or four trajectories of aggression for boys. Several studies have identified a small group of boys who exhibit problematic levels of aggression at the initial assessment (usually kindergarten or first grade) but decrease in aggression over time (for example, Broidy et al., 2003; Maughan et al., 2000; Nagin and Tremblay, 1999; Shaw et al., 2003). The present finding that a small group of boys (12.9 percent of all boys in the sample) comprises the HD trajectory is consistent with these previous efforts. The second trajectory group identified in the BPP data describes the behavior of the majority of the sample boys (65 percent). Again, this sizeable group is not the first to emerge from examinations of aggression trajectories, though there is a fair amount of variation in the direction of growth identified for this trajectory. The MI group identified here shows increasing aggression over time, but the rate of growth is quite moderate. Finally, the low aggression group is ubiquitous in aggression trajectory research.

Three trajectories of aggressive behavior were identified for girls as well. One group of girls displays a high but declining pattern analogous to the HD trajectory for boys. Interestingly, the level of aggressive behavior displayed by these girls at the beginning of first grade is comparable to that displayed by boys. This replicates the findings of Schaeffer and colleagues (2005), whose previous research on the BPP data established similar initial levels of aggression for boys and girls in the high aggression groups. This finding also distinguishes

the current research from other existing research such as that of Broidy and colleagues (2003), which has generally found that the most aggressive girls are still less aggressive than the most aggressive boys. It is important to note, however, that while the pattern of behavior itself is similar for boys and girls, it describes only 8.3 percent of girls compared to 13 percent of boys. The second trajectory for girls describes moderate levels of aggression, and is also notably similar to the boys trajectory. For both sexes, this is the modal pattern of behavior, exhibited by roughly 65 percent of boys and 62 percent of girls. Initial aggression ratings are slightly lower for girls (TOCA-R=1.77 for girls, 1.95 for boys), and remain constant over time. The third trajectory group for girls, the LS group, is directly analogous to the non-aggressive trajectory for boys. Students in these trajectories are non-aggressive at the start of first grade and remain so through third grade. There is a difference in prevalence for this group, which represents the behavior of 21.6 percent of boys and 29.5 percent of girls.

The findings discussed thus far point to the existence of empirically identifiable sub-groups of individuals who differ according to their patterns of aggressive/disruptive behavior over time. Evidence that individuals display different levels of behavior and different rates of change in that behavior over time is not particularly controversial or novel. Thus far, I have simply presented a stylized description of observed behavior. If the existence of such groups is to have meaning for criminology theory or prevention practices, we must examine whether they vary systematically with respect to both their antecedents and their outcomes. Critics of group-based quantitative methods like GGMM argue that latent classes are modeling random variation or "noise". Such "random developmental noise" is undeniably a component of the interaction between the individual and environment that defines development (Lewontin, 2000: 35-36 as cited in Sampson and Laub, 2005b: 40). It is

unlikely, however, that the observed patterns are identified entirely on the basis of random noise. The next stage of analyses tested the validity of that criticism by looking at the relationship between several theoretically derived predictors of problem and antisocial behavior and membership in each latent class. If the estimated models identified patterns of behavior based on random noise, there should be no systematic relationship between the antecedents of problem behavior and the trajectory describing that behavior.

The Influence of Risk Factors on Aggression Trajectories

The dichotomous measure of race exhibited a significant relationship only for boys in the MI trajectory group. The finding that Nonwhite status is associated with a higher probability of membership in the MI group relative to the LI group is consistent with findings from previous research that African-American youth[15] tend to be rated higher on externalizing behaviors (Zimmerman, Khoury, Vega and Gil, 1995). This suggests that teachers may rate Nonwhite students higher on aggressive behavior compared to White students, even when the actual levels of behavior are the same. It is also possible that this finding is driven, in part, by the high correlation in these data between race and socioeconomic status (r=0.647). Family poverty may disrupt the socialization process in the home and place children at greater risk for aggression. Children from poor homes are also more likely to observe criminality in their neighborhoods, which may interact with vulnerabilities generated in the home to bring about higher levels of aggressive behavior. The non-significant influence of race on trajectory membership for girls may reflect their higher levels of parental monitoring, which provides insulation from criminogenic neighborhood influences. Girls, particularly those from lower-class families, are more closely monitored by their parents (Hagan, Simpson and

[15] Of the 370 Nonwhite boys in the data, 363 are African-American.

Gillis, 1987). The high correlation between race and the variable *lunch*, which was used as a proxy for family SES, may also account for the lack of significant findings with respect to the variable *lunch*. *Age* at first grade entry did not have a significant influence on trajectory membership for boys or girls.

Measures of school readiness and peer rejection showed significant relationships with aggression trajectory membership for boys and girls. Findings support the hypothesis that students who are less prepared for school are more likely to be in the HD and the MI or MS trajectories groups, by a factor of 2.4 and 1.5, respectively for boys, and by 2.4 and 1.4 for girls . This hypothesis was generated based on theoretical perspectives such as those of Loeber and Stouthamer-Loeber (1998), Moffitt (1993) and Patterson and colleagues (1989) that implicate early school failure in the persistence of antisocial behavior. Additional measures would be required to test whether the utility of teacher-assessed school readiness for discerning trajectory membership is a reflection of some underlying neuropsychological deficit, or is indicative of the difficult socialization experiences of children who experience early school failure.

Peer rejection was hypothesized to increase the probability of antisocial behavior by encouraging association with deviant peers, thus providing a social context that models and reinforces antisocial behavior (Patterson et al., 1992). The findings show that peer rejection is strongly associated with HD and MI trajectory membership for boys, and with HD and MS trajectory membership for girls.

Of the parental monitoring and supervision measures, the relationship between monitoring and the HD trajectory group for girls was the only one to emerge as significant. Consistent with the findings of Maughan and colleagues (2000), HD girls were 4.5 times

more likely to report low levels of parental monitoring. Several theories could claim this finding as empirical support. Gottfredson and Hirschi's (1990) General Theory of Crime, for example, identifies a lack of self-control as the primary causal agent in criminal behavior and analogous acts. They believe that self-control develops in early childhood as the result of effective parental practices and supervision. Low parental monitoring as predictive of antisocial behavior is also consistent with Differential Association and Social Learning perspectives (Akers, 1985; Sutherland and Cressey, 1955), which would assert that the freedom afforded by low parental monitoring is likely to result in increased exposure to delinquent others. Finally, several current articulations of control theory, such as Sampson and Laub's Age Graded Theory of Informal Social Control, would hypothesize that low parental monitoring during early childhood likely correlates highly with parental attachment. Thus, girls who reported low levels of parental monitoring were at high risk for membership in the HD trajectory because of a lack social bonds to their parents. In addition, the failure to form prosocial bonds with one's own parents may attenuate the likelihood of forming social bonds in other relationships, so from a developmental perspective, this risk factor for girls may mark the beginning of a highly detrimental "cumulative continuity" (Sampson and Laub, 1992). This finding contrasts with that of Heimer and Decoster (1999), who found that low parental supervision was directly related to self-reported violent behavior for males, but was only indirectly related for females.

In summary, several risk factors demonstrated significant relationships with class membership: race, school readiness, peer rejection, and parental monitoring. Taken together these findings constitute support for the notion that the distinct patterns of behavior identified

by the growth models are more than just random noise, and knowledge of an individuals' most likely class membership may have some practical utility.

The Influence of Aggression Trajectories on Offending Outcomes

The three identified trajectories were further validated by their ability to delineate the risk of several measures of juvenile offending. Consistent with previous empirical work (for example, Broidy et al., 2003, Maughan et al., 2000; Nagin and Tremblay, 1999; Petras et al., 2004b; Schaeffer et al., 2003) and with theoretically derived expectations, 85 percent of the boys in the non-aggressive trajectory group during elementary school avoided arrest from ages ten through eighteen, and 90 percent were never arrested for a violent offense. Girls in the non-aggressive group showed similar continuity of prosocial behavior, with almost 93 percent never experiencing arrest and 94 percent never experiencing arrest for a violent offense. For boys, membership in either the MI or HD trajectories was associated with increased risk of offending. Both groups exhibit a higher prevalence of arrest and violent arrest than exhibited by the aggregated sample of boys. While membership in the moderate trajectory distinguished boys from their non-aggressive peers, girls in the moderate trajectory were not distinguishable from non-aggressive girls on distal outcomes. Not so for girls in the HD trajectory, 37.3 percent of whom were arrested during the ten to eighteen age range, and 29.3% of whom were arrested for a violent offense. The finding that girls in the HD trajectory were arrested at the same rate as boys in the HD trajectory is unique to this study.

Membership in the MI and the HD trajectories was shown to significantly increase the risk of early onset (defined for boys as prior to age fifteen). Twenty-one percent of boys in the HD group, and 15 percent of the MI group were arrested before their fifteenth birthday,

compared to six percent of the LI boys. In light of the remarkable predictive relationship between early onset and serious, long-term offending, the results for the HD group deserve particular consideration. When an early age of onset is viewed as a mediating predictor between early childhood aggression and long-term patterns of offending, these results identify a non-trivial group of boys who are identified as being at the extreme-high end of the risk continuum by the end of third grade.

The relationship between aggression trajectories and age of onset for girls is also compelling. Only one trajectory, HD, puts girls at increased risk for early onset (defined for girls as arrest before age fourteen), but the magnitude of the relationship is notable. More than 24 percent of the girls in the HD trajectory experience early onset, compared to less than five percent of girls in either the MS or LS groups. Notice, too, that a higher percentage of girls than boys in the HD group experience early onset. Again, there are profound implications for prevention based on this observed relationship between patterns of aggressive behavior in elementary school and juvenile offending outcomes.

Three distinct behavioral trajectories identified separately for boys and girls are meaningfully associated with both antecedent risk factors and distal outcomes. These findings support the notion that the growth mixture models have identified meaningful sub-groups of individuals who are differentiated from one another not only with respect to their observed behavior, but also with respect to the causes and consequences of it.

Gender and Aggression: Similarities and Differences for Boys and Girls

The empirical landscape of aggression trajectory research for girls is such that replication is required before refinement is a reasonable pursuit. Research on the

developmental course of aggression in girls is limited, and the findings of research to date do not allow for consistent conclusions. At the descriptive level, existing research shows that girls exhibit lower average levels of aggression, and they have a lower prevalence of offending from ages ten through eighteen. In this regard, the research reported here is consistent with established findings. The three trajectories of aggressive behavior identified for girls have also been previously identified, though perhaps in varying combinations.

The general impression conveyed by existing research is that girls are different in initial levels, rate and shape of growth, and association with later behavior. The current research, however, supports the conclusion that girls are more similar to boys than different. These findings contribute to a small but growing body of research that finds similar patterns of aggressive behavior for boys and girls (for example, Schaeffer et al., 2005), and similar linkages between trajectory membership and distal offending outcomes (for example, see Fergusson and Horwood, 2002; Maughan et al., 2000). This discussion is not intended to suggest that the development of aggression, antecedents, and consequences of it are identical for girls and boys. Gender differences in growth for the respective moderate and low aggression classes are observed, parental monitoring exerts an influence on the HD group for girls but not for boys, and the probability of distal outcomes are not differentiated for the girls' MS and LS groups. Nevertheless, the similarities that do emerge are notable because

they are contrary to one of the few consistent findings to emerge from the literature on girls – that their childhood aggression is not as strongly related to juvenile offending compared to boys (for example, Broidy et al., 2003). In fact, the similarities observed between girls and boys in these data pertain to the most problematic group – those who exhibit high levels of aggression and elementary school and more offending during the teen

years. This group is also the primary candidate for prevention and intervention efforts. Interestingly, when analysis included a measure of adult offending, results for girls were dramatically different than for boys and were more consistent with existing research. Given the interest in facilitating earlier desistance, however, the findings from analyses limited to the teenage years are important.

An important consideration regarding the differential strength of the relationship between childhood patterns of aggressive behavior and later outcomes is that the measure of aggression provided by the TOCA-R does not distinguish between overt and relational aggression. Overt, or physical, aggression is behavior that harms or threatens to harm others physically (Crick and Grotpeter, 1995). Pushing and hitting, or threatening to beat up another, for example, are behaviors that constitute overt aggression. Relational aggression, on the other hand, is intended to hinder affiliative and intimacy goals by inflicting harm on others through manipulation or control of relationships (Crick, Casas and Mosher, 1997). Relational aggression may take the form of threats to withdraw friendship, social exclusion, and rumor-spreading. Research suggests that overt aggression is more prevalent among boys, while girls are more likely to engage in relational aggression (Crick, 1997; Crick et al., 1997; Tiet, Wasserman, Loeber, McReynolds and Miller, 2001). This is a potentially important gender difference, as research also suggests that overtly aggressive children are more likely to

experience maladaptive behavioral outcomes than are relationally aggressive children (Crick, 1997). It may be the case that teachers assess boys with respect to their gender normative form of aggression (overt) and girls with respect to theirs (relational). If this is in fact the case, then the lower prevalence of juvenile offending outcomes and the virtual absence of adult incarceration of aggressive girls is perhaps less notable.

Early Childhood Aggression and Desistance

Bushway and colleagues define desistance as "the process of reduction in the rate of offending from a nonzero level to a stable rate empirically indistinguishable from zero" (2003:133). If the focus on offending is extended to include antisocial behavior in general, then this definition of desistance describes the pattern of behavior exhibited by the High-Declining groups of boys and girls in the BPP data. Although they were not observed at a zero-state of aggressive behavior, there can be no question that they were following a desisting pattern of behavior during the period between entry to first grade and the end of third grade. If these boys and girls were in fact experiencing the developmental process of desistance during elementary school, one might reasonably speculate that their risk for later offending behavior is significantly lowered, despite the high risk associated with their initial levels of aggression. The conceptual framework underlying driving this speculation is homotypic continuity, which refers to the continuity of similar behaviors over time (Caspi and Bem, 1990). Applications in criminology emphasize the continuity of antisocial behavior, and conceptualize the various manifestations of problem behavior over time as age-graded expressions of an underlying syndrome of antisocial behavior. Thus, if the boys and girls in the High-Declining trajectories did in fact desist from their aggressive behavior during elementary school, the idea of homotypic continuity allows for the possibility that they have desisted from the larger complex of antisocial behaviors. The alternative possibility is that aggression during elementary school is a distinct behavior, which, while phenotypically similar to juvenile offending, is more than just an age-graded expression of the same underlying syndrome (see, for example, Stanger, Achenbach and Verhulst, 1997). If this is

the case, then desistance from aggression during elementary school has less bearing on the expectation of juvenile offending.

Despite the declining levels of problem behavior observed for the boys and girls in the HD groups, they went on to experience early onset and high rates of offending that significantly distinguish them from their peers. The conclusion, therefore, is that desistance from aggression in childhood does not mitigate the influence of membership in the high aggressive group on offending outcomes. Three possible explanations for this conclusion are plausible. First, it may be the case that childhood aggression and juvenile offending are not age-specific analogous behaviors or expressions of a common underlying trait, so individuals may desist from one behavior but not the other. The second possibility is that the desisting trajectory of the HD groups was interrupted or otherwise incomplete. Analysis of additional assessments beyond third grade would allow for a systematic investigation of this possibility. Finally, recall that a 4-class solution was initially considered as the optimal model to describe the patterns of behavior in these data. If the HD trajectory is also accounting for the behavior of a small group of high-and-chronic aggressive boys and girls, it is possible that the positive association between HD membership and offending outcomes is driven by the continuity of behavior for this small group of individuals.

Methodological Considerations

Human development is inherently complex, and quantitative approaches to studying it involve significant data and modeling demands. The modeling strategy employed here is part of a larger system of latent class growth models, which emerged in response to the need to identify and understand patterns of development over time. These “group-based” strategies

have been applied with increasing regularity in criminological research, and with increased application comes increased attention scrutiny. This critical examination of group-based modeling strategies proves important, as it produced and continues to produce an informative exchange on the interaction of theory and methods (see, for example, Eggleston, Laub, and Sampson, 2004).

The crux of the discussion is embodied in the exchange between Sampson and Laub and Nagin and Tremblay that appeared in the journal *CRIMINOLOGY* (Nagin and Tremblay, 2005a, 2005b; Sampson and Laub, 2005b). The debate is fueled largely by differences in theoretical perspectives; there is staunch disagreement as to whether a general theory can explain criminal behavior across the entire population of offenders, or whether a taxonomic approach that offers distinct etiological hypotheses for sub-groups within the larger population is required. Group-based longitudinal methods have been applied to investigations of the latter perspective with such great frequency that the assumptions attendant to the theoretical perspective have come to be ascribed to the methods themselves. In reality, group-based methods are simply one approach to understanding relationships in longitudinal data. By Sampson and Laub's own account, this analytic strategy is an important tool for "description and pattern recognition" (2005b). Sampson and Laub do not dispute the existence of empirically identifiable patterns of behavior. In fact, they have capitalized on the descriptive power of trajectory analysis in their well-known body of work on the Glueck data (see, for example, Laub and Sampson, 2003; Sampson and Laub, 2003).

The solution appears to be the conscientious and critical application of latent class methods, informed by a thorough understanding of the assumptions, implications, and limits of these modeling strategies. GMM was selected for this research because it provides the

ideal combination of descriptive power for identifying patterns of behavior and flexibility in modeling these patterns. Sampson and Laub caution that trajectories must not be viewed from "a lens of unfolding inevitability" (2005b:14). GMM allows the researcher to acknowledge and address this concern by capturing heterogeneity in development both between and within identified trajectory groups.

The question remains, however, as to what these identified groups actually represent. This is not simply an empirical issue, as suggested by Bauer and Curran's observation that "[t]he fact that multiple latent classes are optimal for the data no more indicates that the population is heterogeneous than a significant correlation indicates that Variable A causes Variable B" (2003a: 358). Here they are referring to whether the identification of finite mixtures within aggregated data represent real groups, or simply account for a non-normal and complex distribution for a homogenous population, but their comment has implications for theory as well.

With respect to gender, the modeling technique employed treats gender as a covariate (i.e. the *Multiple Indicator Multiple Causes*, or MIMIC approach; Joreskog and Goldberger, 1975). MIMIC models require that the number of trajectory groups identified, the structure of each trajectory group, and the predictive accuracy of each trajectory to distal outcomes be covariate-invariant. Such restrictions are not always reasonable and may be contrary to theoretically derived hypotheses. The trajectory groups identified here do appear to meet these criteria fairly well, with the possible exception of their relationships with distal outcomes. However, this assessment is based only on informal observation and is not explicitly tested. Multiple Groups Analysis (MGA) offers a solution to this issue by estimating separate GGMM for each value of a covariate and comparing the key parameters

for these separate models. On the basis of these comparisons, a single model including all values of the covariate is then estimated where parameters can be constrained to be equal or allowed to vary by covariate value. For an example of MGA with these data, see Schaeffer et al., 2006.

Strengths and Limitations

The Baltimore Prevention Data represent a unique sample for this research in that it comprises an epidemiologically defined sample of ethnically diverse boys and girls from an urban area who were socialized during the 1980s and early 1990s. Few studies of developmental patterns include girls in their sample (cf. Broidy et al., 2003; Cote et al., 2001; Schaeffer et al, 2005), making explicit tests of gender differences rare. In addition, much of the existing body of research is based on analysis of Caucasian youth (e.g., Maughan et al, 2000; Nagin and Tremblay, 1999; Shaw et al., 2003; cf. Loeber, Farrington, Stouthamer-Loeber, Moffitt and Caspi, 1998), calling into question the generalizeability of findings to other ethnic populations.

The methods are ideally suited to investigate the relationship between patterns of childhood aggression and later desistance from offending. The use of trajectories of childhood aggression allows for more complete measurement of the independent variable than that obtained with the use of static measures, and the utility of this approach for linking childhood trajectories to offending outcomes emerged. Finally, several person-centered statistical methods for identifying distinct patterns of development are available; Growth Mixture Modeling was selected because it offers a distinct advantage in allowing for class-specific variation. GMM also allows for the possibility of early prediction of class membership based on covariates.

The strengths of the current research are considerable, but of course there are also limitations in these data which must be acknowledged. One of the strengths of the data, for example, may also be viewed as a limitation, in that the results of this research are generalizable only to similar populations of urban children in ethnically diverse school setting. Other limitations arise from the data. For example, assessments of aggression begin in first grade, when the subjects are just over six years old, on average. It would be ideal to have observations from kindergarten or prior to school entry, both for the purposes of identifying trajectory membership and for prevention purposes. This limitation is mitigated to the extent that five time points are available, and these provide ample information for trajectory identification.

A second limitation is manifest in the measures of juvenile offending or non-offending. Official data to age eighteen provides only a short (but critical) window during which arrest outcomes are observed. Use of official records is advisable in that they eliminate concerns of recall and truthfulness in reporting, which are problematic with self-report data. Official records can be problematic, however, in several ways. With respect to examinations of the age of onset of criminal behavior, official records do not allow for the possibility that actual offending likely does occur before official contact (Loeber and LeBlanc, 1990). Farrington (1983) states explicitly that official data cannot reveal when a criminal career actually begins. The probability of detection and processing by the juvenile justice system is low (Weis, 1986), and the probability of a first occurrence of criminal behavior, that is onset, coming to the attention of the police or juvenile justice officials is even more remote. This results in a censoring of the left-hand side of the age-crime curve (Moffitt, 1993), to the extent that Moffitt et al. (2001) estimated that official data from the Dunedin Study

ascertained age of onset a full three to five years after it had actually occurred. In a discussion of the data obtained in the original Cambridge Study in Delinquent Development, West (1982) reports that 52.6% of those who had self-reported delinquency still had no official charges by age 16. Official data may also be, to some extent, a reflection of the differential vulnerability of some offenders to official processing (Farrington, 1983; Weis, 1986). When official data are used for analysis, it is possible that those factors related to explanations of offending behavior are also related to an individual's likelihood of official arrest and processing (Loeber and Dishion, 1983). In mitigation of these issues, one argument proposes that official data may be used as a valid measure of criminal behavior because it will reflect, in a reliable manner, the differences between individuals in their criminal conduct. The argument concedes that, while not all offending will be captured by official records, across individuals official records are a reliable assessment of their actual involvement in crime in relation to others.

The measure of adult incarceration undeniably identifies only a small portion of those who commit offenses as adults. This limitation is particularly relevant for examinations of desistance, since active offenders not observed in the data may be categorized as desisters. This measure is untenable for any explicit test of desistance. It was examined here, however, only to generate a preliminary picture of the development linking childhood to adulthood. A combination of self-report and official data extending into adulthood would be ideal (Paternoster and Brame, 1997) for a more explicit test of the conceptual model outlined in this research. The measure is still helpful, however, particularly for gender comparisons. The notable difference between males and females in their rates of adult incarceration far exceed that which we might expect to observe based on the differential rates of female incarceration

compared to males. The results are still highly suggestive, then, that females desist from criminal involvement at some point between adolescence and adulthood, and that they do so at higher rates than males.

Finally, several theoretically and empirically driven covariates of childhood aggression and juvenile offending were included in the analyses. However, there are other covariates which would be desirable to include, but which are not assessed in these data. Chief among these would be measures of delinquent peer association, better measures of parenting processes, neighborhood-level socioeconomic status, and personality constructs to assess the influence of neuropsychological deficits.

These limitations research do not nullify the contributions of the current research to our understanding of the relationship between the developmental course of childhood aggression and juvenile offending. Such an understanding is a prerequisite for our attempts to prevent the onset of offending and to encourage or foster desistance, which are the ultimate policy goals for the entire body of juvenile offenders. It is important to ground this research in the larger body of prevention efforts, and to remember what it is we are trying to prevent.

Implications for Prevention

Violent crime rates for juveniles have been steadily dropping since 1994 (Snyder, 2004). Many are heartened, and for good reason, by these declining crime rates. Relief over this seeming "normalization" of rates of violent juvenile offending, however, ought not dampen our efforts to understand and explain juvenile offending, and violent offending in particular.

Youth violence remains a real and significant threat to public health. According to FBI data, juveniles accounted for 15 percent of all violent crime arrests in 2002 (Snyder, 2004). This figure is daunting when viewed in light of the evidence that less than half of all serious violent crime committed by juveniles is reported to law enforcement (Snyder and Sickmund, 1999), and is therefore presumably not reflected in these FBI data. Juveniles are also disproportionately affected as victims of violence. Data from the National Longitudinal Study of Adolescent Health (Add Health) indicate that homicide is the second leading cause of death among adolescents. By comparison, homicide is the 10th leading cause of death for the population as a whole (Blum, Ireland and Blum, 2003).

Recent evidence also suggests that those juveniles becoming involved with the system are getting younger and younger (Snyder et al., 2003), with increasing evidence of children under the age of 13 becoming involved in serious and violent delinquency. One recent investigation shows a 45 percent increase in arrests for violent crimes among very young juveniles (Snyder et al, 2003). Despite the welcomed downward trend in juvenile involvement in violent crime, the need to understand and address youth violence remains exigent.

Contributing to the necessity of a thorough and sensitive examination of the role of childhood development in later desistance is the changing face of female involvement in serious and violent delinquency. Girls' levels of involvement in delinquency, including violence, has been increasing in recent years (Bureau of Justice Statistics, 1999; Hipwell et al., 2002; Tatem-Kelly, Huizinga, Thornberry and Loeber, 1997), making the development of aggression and offending in girls an ever more relevant consideration.

Juveniles continue to be overrepresented in violent crime statistics and to offend at higher rates than the rest of the population. The consequences of violent crime are no less dire than they were in decades past, and even in the face of overall declining rates, evidence suggests that youth violence is becoming a more problematic reality for certain segments of the juvenile population, including females. The research presented here contributes to the development of a theoretical understanding of the influence of early development on later desistance. The ultimate goal is the application of sound theory to prevent juveniles from becoming involved in criminal behavior and to redirect those who have already done so toward prosocial pathways.

Appendix A

Latent Class Growth Analysis

Latent Class Growth Analysis (LCGA) is a form of finite mixture models that represents a special case of GMM where the variance of the slope and intercept (the growth parameters) are zero. This means that everyone within each class is constrained to the same slope and intercept.

Table A.1 Fit Indices for LCGA Analysis

	Boys (n=591)				
Classes	BIC	SSABIC	Entropy	ALRT p-value	LL (# parameters)
1	5520.763	5504.763	---	---	-2744.402 (5)
2	5214.656	5189.259	0.758	0.0000	-2581.761 (8)
3	5142.867	5107.945	0.715	0.0183	-2536.278 (11)
4	5121.386	5076.940	0.759	0.1403	-2515.950 (14)
5	5109.934	5055.964	0.752	0.7206	-2500.635 (17)
6	5115.009	5051.515	0.748	0.0204	-2493.585 (20)
7	5126.693	5053.675	0.759	0.0180	-2489.840 (23)
8	5147.976	5065.434	0.582	0.1888	-2490.893 (26)
9	5159.056	5066.989	0.565	0.5000	-2486.845 (29)
	Girls (n=581)				
1	4484.946	4469.073	---	---	-2226.561 (5)
2	4115.598	4090.201	0.894	0.0001	-2032.340 (8)
3	4055.213	4020.292	0.847	0.3315	-1992.600 (11)
4	4004.227	3959.782	0.813	0.1611	-1957.560 (14)
5	3969.692	3915.723	0.834	0.0001	-1930.745 (17)
6	3988.786	3925.293	0.751	0.5018	-1930.745 (20)
7	3954.792	3881.775	0.800	0.2717	-1904.201 (23)
8	3965.645	3883.105	0.839	0.0000	-1900.081 (26)
9	3971.134	3879.070	0.647	0.0719	-1893.278 (29)
10	4012.074	3910.487	0.643	0.3952	-1904.201 (32)

In addition, residual variances cannot vary over time and space. Results from the LCGA analysis are summarized in Table A.1.

In the case of males, it is readily evident that no specific class solution is fully endorsed across the spectrum of fit indices. The BIC points toward a 5-class solution while the SSABIC recommends a 6-class solution, the ALRT favors a 7-class solution, and none of the solutions reaches a satisfactory minimum entropy of 0.80. The 5-class solution for males is disqualified from consideration by the ALRT statistic ($p = 0.7206$). In the absence of a clear best solution, the decision between the 6- or the 7-class solution may depend upon other considerations. Class prevalences, the number of persons likely represented by each class, may be helpful in directing this decision.

Turning now to the LCGA results for females: perhaps surprising is the consistent support for a 5-class solution. Entropy for the 5-class solution is acceptable at 0.834 (though acceptable entropy does not distinguish the 5-class solution from many others).

Modification indices suggest that a better-fitting and more parsimonious solution may be obtained if the variances of the growth parameters and the residuals of the indicators are allowed to vary. Estimation of these parameters, however, renders the model in violation of the assumptions of the LCGA approach and requires the application of a *Variance Homogeneity* model, which estimates variances for the intercept and slope parameters but constrains these variances to be equal for all classes. Variance homogeneity models also estimate residual variances for the latent class indicators and allows these parameters to vary across class, but not time.

Variance Homogeneity Models

For males, the 4-class solution is strongly endorsed over all others. The 4-class solution shows the lowest BIC (6049.824) and a significant ALRT (p = 0.0126), indicating that the 4-class solution is significantly better than a 3-class solution. Although the ALRT suggests that the 5-class solution is an improvement over four classes, the larger BIC and lower entropy for the 5-class solution mean that the 4-class model is maintained as the best fit.

Table A.2 Fit Indices for Variance Homogeneity Models

	Boys (n=591)				
Classes	BIC	SSABIC	Entropy	ALRT p-value	LL (# parameters)
2	6135.837	6062.819	0.853	0.0899	-2994.412 (23)
3	6089.159	5984.394	0.769	0.0008	-2939.113 (33)
4	6049.824	5913.311	0.882	0.0126	-2887.486 (43)
5	6098.499	5930.239	0.779	0.0000	-2879.864 (53)
6	6110.074	5910.067	0.745	0.2892	-2853.691 (63)
7	6105.473	5873.719	0.778	0.1502	-2819.432 (73)
	Girls (n=581)				
2	5083.177	5010.160	0.906	0.0040	-2468.394 (23)
3	5028.546	4923.784	0.865	0.1794	-2409.255 (33)
4	5006.704	4870.195	0.846	0.1343	-2366.510 (43)
5	5017.330	4849.075	0.868	1.0000	-2339.999 (53)
6	5031.999	4891.998	0.827	0.5871	-2315.510 (63)
7	5038.912	4807.165	0.786	0.4114	-2287.142 (73)

The best model for girls is less evident. The BIC is lowest for the 4-class solution, while the SSABIC continues to drop up to and beyond the 7-class solution.[16] Entropy for all

[16] Additional class models were not estimated after the 7-class solution because other fit indices strongly disallow a solution with more than 6 classes (i.e. ALRT of 1.00 for the 6-class model).

the females' models is acceptable, with the 2-class solution generating the best classification accuracy. The 2-class solution is also the only model endorsed by the ALRT (p = 0.0040).

Table A.3 presents the model parameters for the boys 4-class solution, and illustrates the restrictions imposed by the variance homogeneity approach. For example, the variance estimates for the intercept (.074, t = 1.675) and slope (.107, t = 6.238) apply to each of the four classes. The intercept variance is small in relation to the estimated intercepts of 1.228, 2.165, 3.231and 4.700, and is non-significant, which suggests that there is minimal variation around the starting point within each class.

Table A.3 Males 4-class Solution Model Parameters – Variance Homogeneity

Class	Class Size	Intercept	Slope	Intercept Variance	Slope Variance
1	35	4.700*	-0.729*	.074	.107*
2	80	3.231*	-0.116		
3	282	1.228*	.304*		
4	200	2.165*	.167*		

* Significant at $p \leq .05$

The variance for the slope, however, is non-trivial and statistically significant. This suggests that there is a notable amount of variation within each class in the actual rate of growth or development over time. The restrictions of the variance homogeneity model, however, are such that the possibility of different variances by class cannot be further explored. Modification indices suggest that estimating the variance of the growth parameters and the residual variables separately for some of the classes could significantly improve model fit. If these modifications are applied, the models have then become variance heterogeneity models. As the name implies, variance heterogeneity models of longitudinal development allow for

estimation of unique variances associated with each class-specific growth parameter. Any combination of distinct intercept and slope variances is possible. In addition, separate variances may be estimated for the residuals of each of the latent class indicators, both within and across classes. As such, variance heterogeneity models are synonymous with Growth Mixture Models. Certainly, estimation of a variance heterogeneity model can become a rather daunting, if not altogether haphazard endeavor. The effort and care required is only justified in the face of sufficient motivation from "precursor" models, such as the variance homogeneity model just discussed. In this case, modification indices suggest that the models may be greatly improved by capitalizing on the flexibility of the variance heterogeneity model.

Appendix B

Table B.1 Parameter Estimates for Three-Class Model, *Race* Excluded: Boys (n=597)

	Aggression Growth Estimates					
	High-Declining		***Moderate-Increasing***		***Non-Aggressive***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.950	0.184*	1.953	0.079*	1.049	0.021*
α_1	-0.368	0.125*	0.209	0.042*	0.198	0.087*
$V(\zeta_0)$	0.242	0.033*	0.242	0.033*	0.005	0.002*
$V(\zeta_1)$	0.031	0.028	0.031	0.028	0.031	0.028
γ_{lunch}	0.993	0.461	0.536	0.285	---	---
γ_{age}	-0.841	0.504	-0.435	0.295	---	---
γ_{ready}	0.892	0.212*	0.433	0.179*	---	---
γ_{reject}	3.019	0.430*	2.067	0.390*	---	---
$V(\varepsilon_{1F})$	0.196	0.033*	0.196	0.033*	0.000	Fixed
$V(\varepsilon_{1S})$	0.320	0.037*	0.320	0.037*	0.018	0.011
$V(\varepsilon_{2F})$	0.678	0.104*	0.678	0.104*	0.428	0.087*
$V(\varepsilon_{2S})$	0.949	0.100*	0.949	0.100*	0.598	0.128*
$V(\varepsilon_{3S})$	0.995	0.196*	0.995	0.196*	0.222	0.232
$C(\varepsilon_{1F,} \varepsilon_{1S})$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$C(\varepsilon_{2F,} \varepsilon_{2S})$	0.459	0.099*	0.459	0.099*	0.459	0.099*
$C(\alpha_{0,} \alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	1.171	0.372*	0.805	0.143*	1.114	0.282*
τ_{rules}	-0.382	0.308	-0.406	0.133*	-0.419	0.233
Class Prevalence	0.1271 (n=76)		0.6582 (n=393)		0.2146 (n=128)	

LL = -2724.042, df=35 BIC = 5671.801 Entropy = 0.877 BLRT = 0.000

* $p<0.05$

Table B.2 Parameter Estimates for Three-Class Model, *Lunch* Excluded: Boys (n=597)

	Aggression Growth Estimates					
	High-Declining		***Moderate-Increasing***		***Non-Aggressive***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.951	0.167*	1.953	0.070*	1.048	0.019*
α_1	-0.390	0.107*	0.212	0.040*	0.198	0.079*
$V(\zeta_0)$	0.245	0.031*	0.245	0.031*	0.005	0.002*
$V(\zeta_1)$	0.030	0.025	0.030	0.025	0.030	0.025
γ_{race}	0.778	0.474	1.012	0.263*	---	---
γ_{age}	-0.967	0.504	-0.454	0.301	---	---
γ_{ready}	0.906	0.209*	0.447	0.172*	---	---
γ_{reject}	2.819	0.404*	1.910	0.373*	---	---
$V(\varepsilon_{1F})$	0.189	0.032*	0.189	0.032*	0.000	Fixed
$V(\varepsilon_{1S})$	0.322	0.038*	0.322	0.038*	0.019	0.010
$V(\varepsilon_{2F})$	0.684	0.106*	0.684	0.106*	0.430	0.088*
$V(\varepsilon_{2S})$	0.951	0.100*	0.951	0.100*	0.606	0.132*
$V(\varepsilon_{3S})$	0.993	0.182*	0.993	0.182*	0.228	0.211
$C(\varepsilon_{1F,}\varepsilon_{1S})$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$C(\varepsilon_{2F,}\varepsilon_{2S})$	0.465	0.102*	0.465	0.102*	0.465	0.102*
$C(\alpha_{0,}\alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	1.143	0.359*	0.807	0.142*	1.123	0.277*
τ_{rules}	-0.433	0.315	-0.389	0.133*	0.436	0.232
Class Prevalence	0.1276 (n=76)		0.6566 (n=392)		0.2158 (n=129)	

LL = -2719.165, df=35 BIC = 5662.048 Entropy = 0.879 BLRT = 0.000

* $p<0.05$

Table B.3 Parameter Estimates for Three-Class Model, *Lunch* Excluded: Girls (n=581)

	Aggression Growth Estimates					
	High-Declining		***Moderate-Stable***		***Low-Stable***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.690	0.170*	1.774	0.046*	1.058	0.020*
α_1	-0.410	0.109*	0.048	0.027	0.066	0.018*
$V(\zeta_0)$	0.129	0.023*	0.129	0.023*	0.000	Fixed
$V(\zeta_1)$	0.002	0.003	0.002	0.003	0.002	0.003
γ_{race}	1.303	0.781	0.289	0.248	---	---
γ_{age}	-0.728	0.537	-0.241	0.237	---	---
γ_{ready}	0.927	0.209*	0.338	0.119*	---	---
γ_{reject}	1.971	0.365*	0.856	0.263*	---	---
$V(\varepsilon_{1F})$	0.215	0.033*	0.215	0.033*	0.007	0.004
$V(\varepsilon_{1S})$	0.263	0.038*	0.263	0.038*	0.013	0.004*
$V(\varepsilon_{2F})$	0.417	0.058*	0.417	0.058*	0.145	0.042*
$V(\varepsilon_{2S})$	0.415	0.041*	0.415	0.041*	0.283	0.069*
$V(\varepsilon_{3S})$	0.664	0.075*	0.664	0.075*	0.077	0.030*
$C(\varepsilon_{1F,}\varepsilon_{1S})$	0.006	0.003*	0.006	0.003*	0.006	0.003*
$C(\varepsilon_{2F,}\varepsilon_{2S})$	0.192	0.051*	0.192	0.051*	0.192	0.051*
$C(\alpha_{0,}\alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	0.371	0.408	1.886	0.183*	1.888	0.263*
τ_{rules}	-0.768	0.433	-0.072	0.121	-0.036	0.178
Class Prevalence	0.0822 (n=48)		0.6223 (n=361)		0.2954 (n=172)	

LL = -2062.379, df=36 BIC = 4353.888 Entropy = 0.908 BLRT = 0.000

* $p<0.05$

Table B.4 Parameter Estimates for Three-Class Model, *Race* Excluded: Girls (n=581)

	Aggression Growth Estimates					
	High-Declining		***Moderate-Stable***		***Low-Stable***	
Parameter	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
α_0	3.682	0.169*	1.772	0.046*	1.059	0.020*
α_1	-0.416	0.109*	0.049	0.027	0.066	0.019*
$V(\zeta_0)$	0.129	0.023*	0.129	0.023*	0.000	Fixed
$V(\zeta_1)$	0.002	0.003	0.002	0.003	0.002	0.003
γ_{lunch}	0.798	0.518	0.024	0.215	---	---
γ_{age}	-0.695	0.528	-0.255	0.237	---	---
γ_{ready}	0.880	0.210*	0.339	0.120*	---	---
γ_{reject}	1.984	0.354*	0.895	0.268*	---	---
$V(\varepsilon_{1F})$	0.213	0.032*	0.213	0.032*	0.007	0.004
$V(\varepsilon_{1S})$	0.262	0.038*	0.262	0.038*	0.013	0.004*
$V(\varepsilon_{2F})$	0.422	0.059*	0.422	0.059*	0.145	0.042*
$V(\varepsilon_{2S})$	0.415	0.041*	0.415	0.041*	0.284	0.069*
$V(\varepsilon_{3S})$	0.664	0.075*	0.664	0.075*	0.076	0.031*
$C(\varepsilon_{1F,}\varepsilon_{1S})$	0.006	0.003*	0.006	0.003*	0.006	0.003*
$C(\varepsilon_{2F,}\varepsilon_{2S})$	0.193	0.051*	0.193	0.051*	0.193	0.051*
$C(\alpha_{0,}\alpha_1)$	0.000	Fixed	0.000	Fixed	0.000	Fixed
$\tau_{monitor}$	0.365	0.405	1.893	0.185*	1.888	0.262*
τ_{rules}	-0.783	0.426	-0.070	0.122	-0.036	0.178
Class Prevalence	0.0835 (n=48)		0.6196 (n=360)		0.2969 (n=173)	

LL = -2063.408, df=36 BIC = 4355.947 Entropy = 0.907 BLRT = 0.000

* $p<0.05$

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