ARE "DYNAMIC" PREDICTORS OF YOUTH VIOLENCE ACTUALLY DYNAMIC?

AN INNOVATIVE APPROACH TO MODELING CHANGE

A Thesis

Presented to

The Faculty of the Department

of Psychology

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Master of Arts

By

Jessica Klement Davis

August 2015

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ABSTRACT

Youth violence is a serious social problem with a 12-month prevalence rate of about 35 percent (Herrenkohl, Lee, & Hawkins, 2012). While research has identified dynamic predictors of violence, there is little evidence of their malleability and impact on youth violence since experimental studies are scarce and few correlational studies have examined within-individual differences. Also, few studies have applied item response modeling (IRM), which allows differential weighting of violent acts. The current study is the first to use multilevel modeling (MLM) to examine predictors of within-individual change in violence among males in the National Longitudinal Study of Adolescent Health (Add Health) data set. Due to sex differences in the rates of violent offending, the sample is restricted to males. It is only the second study to use IRM to scale the violence outcome measure. The sample includes males (N=2288) from the Add Health public dataset, which captures violent offending from Wave 1 (age 11-21) to Wave 2 (age 12-22). Samejima's (1997) graded response model translated self-reported violence onto a continuous scale. MLM examined dynamic predictors of within-individual change in violence, static predictors of between-individual differences, and the interaction between age and peer delinquency. The IRM results showed that items varied in difficulty, poor factor loading for one item, and local dependence for two other items. The results of MLM indicated that, on average, individuals became less violent with age; Peer delinquency, a daily family meal, and alcohol use significantly predicted within-individual change in violence; and demographic variables, GPA, school attachment, history of grade retention, depressive symptoms, peer delinquency, and a daily family meal significantly predicted the level of violence between individuals.

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Are “Dynamic” Predictors of Youth Violence Actually Dynamic?

An Innovative Approach to Modeling Change

Violent offending is a serious health problem, which peaks around age 18 to 24, and leads to physical injury, psychological trauma, and death (Lauritsen & Rezey, 2010). The National Research Council defines violence as “behaviors that intentionally threaten, attempt or inflict physical harm on others” (Dahlber & Potter, 2001). According to the latest estimates by the CDC (2010), homicide is the second leading cause of death for youth aged 15 to 24 years old. Although the CDC reported declines in the non-fatal assault-related injuries among persons 10 to 24 years from 2001 to 2011, the rate remains nearly two times higher among youth 10 to 24 compared to all other ages (Youth violence: National statistics, 2013).

Research indicates that a subset of youth with an early age of onset commit more crimes and persist into adulthood (Moffitt, 1997). The estimated monetary value of saving a single 14-year-old high risk juvenile from a life of crime ranges from $2.6 to $5.3 million (Cohen & Piquero, 2008). While these crimes are not exclusively violent, non-violent delinquency is also a predictor of future violence (Herrenkohl, Lee, & Hawkins, 2012). The key to reducing youth violence is to identify dynamic risk and protective factors of violence perpetration with causal implications.

There is little evidence of the malleability of dynamic predictors and their effect on youth violence due to the fact that experimental studies are scarce and most correlational designs examine mean differences between individuals. A risk factor predicts an increase in violence, while a protective factor predicts a decrease or low level of violence. Most research on predictors of violence has used cross-sectional or retrospective designs, but prospective longitudinal designs, which allow the estimation of dynamic processes, are preferred (Lösel &Farrington, 2012). Traditionally, longitudinal studies have used a multivariate approach to analyze within-individual change, which require a balanced, repeated-measures design. This assumption of equal time-points, equal sample sizes, and equal number of observations is difficult to meet in longitudinal research. Multilevel modeling (MLM) is once method for analyzing individual change and its relations with dynamic and fixed variables in multi-wave data that doesn't require the assumption of a balanced design (Bryk & Raudenbush, 1992; as cited in Francis, Schatschnieder, & Carlson, 2000).

The current research is driven by theory in developmental and life-course criminology (DLC) and intends to understand change mechanisms that occur across development when violent offending is most malleable. The sample includes males from the National Longitudinal Study of Adolescent Health (Add Health) public dataset, which captures violent offending from age 11 to 21 at Wave 1 to age 12 to 22 at Wave 2. Self-reported violence was translated onto a continuous scale using item response modeling (IRM) in order to permit more sophisticated statistical analyses. MLM examined dynamic variables that predict change in within-individual violence and static variables that predict differences between individuals.

The aims of the present study were to (a) identify dynamic variables that predict within-individual change in youth violence above and beyond fixed effects; (b) examine whether static and control variables predict differences in violence between individuals; and (c) examine the interaction between peer delinquency and age. Results may inform risk assessment and management.

Review of Literature

An Overview of Developmental and Life-course Criminology

Developmental and life-course criminology (DLC) provides a context for research investigating the development (increase) and desistance (decrease) of violence. Farrington (2006) combines theories from developmental criminology with life-course criminology under the heading developmental and life-course criminology (DLC). DLC is concerned with risk and protective factors that can be targeted in treatment, the development of criminal behavior, how age interacts with risk and protective factors, how life events and transitions affect criminal behavior and the development of risk and protective factors, and research on within-individual changes in offending.

Predictors, which refer to both risk and protective factors, can be categorized as either dynamic or static. A dynamic predictor is changeable and thus can be targeted in interventions. Research on risk factors for recidivism has also identified a subcategory of dynamic risk factors, referred to as criminogenic because they directly increase the likelihood of crime (Benda et al., 2001). Static variables include variables that do not change, such as gender.

Previous Research on Predictors of Youth Violence

Most of the studies looking at predictors of youth violence focus on individual factors, such as academic achievement, neurological deficits, prior victimization, and criminal history. Family, school, and social factors, such as parental supervision, delinquent peers, and school attachment, are also highly related to youth violence perpetration. For purposes of discussion, these predictors can be categorized as either static or dynamic.

Static predictors.

Scores on Intelligence Tests. A low verbal IQ has been linked to violent offending (Guo, Roettger, & Cai, 2008; Moffitt & Caspi, 2001; McNulty, Bellair, & Watts, 2012), but scholars suggest a number of confounds, such as low SES, school environment, self-esteem, and school attachment. Low verbal skills and lack of social bonds in school place youth at risk for violent offending and further disadvantage in competition for employment and admission to college. McNulty and colleagues (2012) found that verbal ability has both a direct effect and indirect effect (through academic achievement) on youth violence. In addition, repeating a grade and having a learning disability (Resnick et al., 2004) are risk factors for youth violence. It is also possible that exposure to violence and violent offending cause academic failure and low verbal ability.

A common explanation for the high prevalence of violence during youth is poor impulse control, which is attributed to the developing prefrontal cortex. The prefrontal cortex, the part of the brain responsible for working memory, planning, and impulse control, is not fully developed until about age 25 (Sowell, Thompson, Holmes, & Jernigan, 1999; as cited in Johnson, Blum, & Giedd, 2009). On the contrary, a study of neurocognitive impairment in boys found no significant group differences on the WCST, a neuropsychological test indicative of frontal impairments, between the following groups in antisocial behavior: control, childhood-limited, adolescent-limited, and life-course persistent (Raine et al., 2005). However, the life-course persistent group had lower verbal IQs, more abuse and neglect, and non-significantly higher rates of Attention Deficit Hyperactivity Disorder (ADHD) (Raine et al., 2005); ADHD ($p=.009$) did not reach significance following a Bonferroni correction of $p=.0083$. Low verbal IQ may outperform low impulse control in the prediction of violent behavior.

History of child abuse and neglect. Caspi and colleagues (2002) found that monoamine oxidase A (MAOA) genotypes moderated the effect of maltreatment on the development of violence in male children; maltreated boys with low MAOA were much more likely to engage in violent behavior. Since Caspi and colleagues' (2002) study, others have replicated their findings of high risk for violence among maltreated children with low MAOA activity (Fergusson et al., 2011; Kim-Cohen et al., 2006). Researchers have also found a direct relationship between a history of child abuse (Loeber et al., 2005) or prior violence victimization (Resnick et al., 2004) and violent offending. While the Add Health public dataset, on which the current study is based, does not allow for examination of this predictor, it is included here due to its prominence in the youth violence literature.

Dynamic predictors.

Academic achievement. Academic achievement appears to exert a mixed effect on youth violence, with high academic achievement (Loeber et al., 2008; Resnick et al., 2004) acting as a protective factor and low academic achievement (Ellickson & McGuigan, 2000; Loeber et al., 2005; Reingle et al., 2013) acting as a risk factor for youth violence.

While the youth violence literature is missing experimental studies related to verbal and academic achievement, Project LEAD reduced recidivism rates among adult inmates by targeting individuals with deficient functional reading levels that made it difficult for them to seek and maintain employment (Williams, 1996). The project provided weekly instruction, computer assisted instruction and classroom instruction, individual academic tutoring, and life-skills sessions.

Depressed mood. Depressive symptoms have been identified as a correlate of youth violence and may exhibit a dynamic effect on violent offending. A depressed mood has been found to increase the risk of violence among male youth (Loeber et al., 2005; Reingle et al., 2013; Reingle, Jennings, and Maldonado-Molina, 2011; Pardini, Loeber, Farrington, & Stouthamer-Loeber, 2012). Alternatively, a low level of depressive symptoms has been identified as a protective factor (Bernat et al., 2012). The relationship between depression and violent behavior is not unusual given the emotion dysregulation and lack of coping skills among offenders. Psychological or emotional disturbance among offenders may result in impulsive acts of violence for some individuals, which can serve as a maladaptive tool for emotion regulation.

Nonviolent delinquency. Violent offenders often begin their criminal “careers” with less severe and non-violent acts of antisocial behavior. The youth violence prediction research has identified non-violent delinquent acts, such as truancy (Loeber et al., 2005) and alcohol and illicit drug use (Loeber et al., 2005; Maldonado-Molina, Reingle, & Jennings, 2011; Resnick et al., 2004; Reingle et al., 2013) as predictors of violence. However, it is difficult to distinguish whether these correlations are measuring a potential causal relationship or an underlying trait that is common to both behaviors.

Parental supervision. Poor parental monitoring has been cited as a risk factor for youth violence and aggression (Dishion & McMahon, 1998; Kim et al., 2011; Loeber et al., 2005; Loeber et al., 2008). Parental monitoring, or supervision, refers to whether the youth’s parents are present when the youth is at home and generally know the youth’s whereabouts. Guo et al. (2008) observed a decreased probability for violent offending among youth in the Add Health sample that had daily meals with at least one parent, which is likely related to parental supervision.

Some evidence, however, shows that the relationship between parental monitoring and child antisocial behavior is reciprocal (Laird, Pettit, Bates, & Dodge, 2003; Stattin & Kerr, 2000; as cited in Dodge, Greenberg, & Malone, 2008). Dodge and colleagues (2008) observed that school failure paradoxically lowered parental monitoring, which, they hypothesized, might be caused by parents' attempt to reduce conflict. Additionally, poor parental monitoring influenced violence directly and indirectly through its effect on delinquent peers (Dodge et al., 2008).

Delinquent peers. Delinquent peers are one of the strongest and most consistent predictors of youth violence and delinquency (Herrenkohl et al., 2003; Loeber et al., 2005). Other peer factors that are related to youth violence include a friend's attempted or completed suicide (Resnick et al., 2004) and peer social rejection (Dodge, Greenberg, & Malone, 2008).

Loeber et al. (2008) stated that "no other factor was so consistently and independently predictive of violence" as peer delinquency among the Pittsburgh Youth Study (PYS) sample (p. 201). Low peer delinquency has also been shown to act as a protective factor (Bernat et al., 2012; Pardini et al., 2012) and, less consistently, as a mixed factor (Loeber et al., 2008). However, there is a paucity of research distinguishing predictors of baseline violent offending and change in violence. Jennings, Maldonado-Molina, and Komro (2010), for example, found that delinquent peers no longer significantly distinguished delinquent trajectories from non-delinquents after controlling for baseline delinquency and demographic variables.

Bernat et al. (2012) suggested that peer delinquency has a diminishing effect on violence perpetration. Bivariate analyses were used to measure the effect of peer delinquency at age 13 on violence involvement at age 14 (Wave 2) and age 18-20 (Wave 3) among a subsample of males and females (N~1226) from the Add Health dataset. Results showed that individuals with a high level of peer delinquency at age 13 were at significant risk for violent offending at age 14 but not 18-20. While Bernat et al. concluded that high levels of peer delinquency were unrelated to violence perpetration in young adulthood; the lack of effect is likely due to the change in levels of peer delinquency across adolescence. In addition, the outcome measure was coded as dichotomous (yes or no) and did not capture variability in the severity of violent acts.

On the contrary, Kroner & Yessine (2013) found evidence that peer delinquency may be causally related to adult recidivism. They examined the correlation between treatment changes among adult offenders under community supervision on recidivism. Interestingly, the Antisocial Associates reliable change score, a subscale of the Measures of Criminal Attitudes and Associates, showed the least amount of change and was not central to the treatment program but was the only measure to predict recidivism.

While peer delinquency has been well established as a predictor of youth violence, little has been done to examine whether within-individual fluctuations in peer delinquency is associated with an increase in violent offending using longitudinal designs. Additionally, few studies have examined whether peer delinquency shows a diminishing or increasing effect on violence across development. Both dynamic processes and their interaction with age have important implications for violence risk assessment and management.

School attachment. Good school attachment, which refers to a youth's satisfaction with their school, teachers, and peers, protects against youth violent offending (Herrenkohl et al., 2012; Resnick et al., 2004). Herrenkohl et al. (2003) found that youth who were aggressive at 15 were less likely to be violent at 18 if they went to religious services and had strong school attachment (as cited in Walker et al., 2013). Frank (2000) examined the effect of attachment relationships on youth violence. He concluded that families, schools, and religious communities provide opportunities for youth to form secure attachments, which reduce violence. It is also possible that secure attachments exhibit their effect on youth violence by protecting against peer delinquency.

Overview of Violence Research with Add Health

The National Longitudinal Study of Adolescent Health (Add Health) is a school-based longitudinal study of adolescents and young adults, beginning in the 7-12th grade. High schools were randomly selected from a sampling frame stratified by size, region, urbanicity, and percent white. The final school sample included 132 schools and 90,118 initial respondents. A subsample, stratified by grade and gender, was selected for in-home interviews, which occurred over four time points. Self-reported violent offending was measured when participants were ages 11 to 21 at Wave 1, 12 to 22 at Wave 2, 18 to 26 at Wave 3, and 24 to 32 at Wave 4. The Add Health public data set includes a subsample (N=6504) from Wave 1 and Wave 2.

Most of the studies examining violence among youth in the Add Health data have used survey logistic regression, multiple regression, or bivariate analyses. Resnick et al. (2004) and Bernat et al. (2012) provide the most extensive analyses, so far, of risk and protective factors from Wave 1 predicting violence at Wave 2, with Bernat et al. including Wave 3. Several studies have examined genetic effects (Beaver et al., 2007; Boutwell & Beaver, 2008; Daigle, 2010; Guo et al., 2007; Guo et al., 2008; Lee, 2011; Vaske, Wright, Beaver, 2010). Several studies have also examined neighborhood effects and racial disparities in violent offending among youth in the Add Health sample (Cui, 2012; Estrada-Martinez et al., 2013; Knoester & Haynie, 2005; Reingle, Jennings, & Maldonado-Molina, 2011). However, none of the studies have analyzed the prediction of within-individual change in violence and, therefore, cannot speak to the dynamic quality of predictors. Additionally, only one study (Cui, 2012) translated the survey responses onto a continuous scale.

Gaps in Knowledge

Traditional methods of examining predictors of violence, such as single time-point or cross sectional studies, cannot assess intraindividual change on a predictor, which is what makes it dynamic. Experimental studies using interventions among youth are scarce and typically use forensic populations, so they cannot examine the development of violence over time. Prospective longitudinal designs are preferred (Lösel &Farrington, 2012) and allow the estimation of the predictive value of dynamic processes. Growth modeling, a type of multilevel modeling, is one method for analyzing individual growth curves (IGCs) and correlates of change in multi-wave data (Bryk & Raudenbush, 1992; as cited in Francis, Schatschnieder, & Carlson, 2000).

There is also little knowledge of how the predictability of risk and protective factors changes with age. Stouthamer-Loeber and colleagues (2008) found that more protective factors measured during age 7-12 predicted early desistance (by age 13-16) compared to intermediate (17-19 years) and late (20-25 years) desistance. While this study included nonviolent recidivism, it seems likely that a similar declining association would be found among violent offenders, which would emphasize the need for early intervention. Since Add

Health included a large sample of youth spanning ages 11 to 22 in the first two waves, we can test the interaction between age and important predictors.

Measuring within-individual change with MLM

Traditional methods of analyzing within-individual change, such as a multivariate approach, require a balanced, repeated-measures design. This assumption of equal time-points, equal sample sizes, and equal number of observations is difficult to meet in longitudinal research. Individuals with missing data are omitted from the multivariate analysis, which lowers power and can create biased estimates (Maxwell & Delaney, 2004).

Multilevel models are more flexible than traditional approaches and can identify dynamic variables that predict growth (within-individual change) in violence while assessing fixed variables that predict differences between individuals. Francis and colleagues (1994) provide a detailed overview of the MLM approach to measuring change. There are several advantages to modeling individual growth with MLM: (1) subject characteristics that correlate with change will correlate to the parameters of individual growth; (2) estimation will improve as the number of waves increase; (3) the reliability of the growth curve can be directly estimated; (4) subjects with missing data at one time point can be included if there are more than two waves of data; (5) subjects do not need to be measured at exactly the same time point; (6) simultaneous intraindividual and interindividual analyses can be conducted; and (7) greater precision in the estimation of within-subjects growth parameters allows greater power in detecting between-subjects effects (Francis et al., 1994). In addition, the error covariance structure can be estimated, reducing the error variance when the appropriate error covariance structure is specified (Shek & Ma, 2011). MLM requires that the following assumptions be met: (a) homogeneity of variance and (b) normality (Raudenbush & Bryk, 2002).

The first step to studying individual change is to formulate an unconditional mean model, which estimates the effect of time as a fixed covariate (see equation 1 below). The fixed effect of time (Y_{10}) estimates the mean rate of change in the outcome. This is also referred to as the fixed slope. The fixed effect of the intercept (Y_{00}) estimates the grand mean, or fixed intercept. Next, an unconditional growth model (see equation 2 below) estimates the random effect of the intercept (U_{0i}), which is the average individual variation around the mean intercept, and the random effect of time ($U_{1i}TIME_{ti}$), which is the average individual variation around the mean slope. The unconditional linear growth model can be broken down into two levels. Level 1 (equation 3) includes random effects, while level 2 includes the fixed effects on the intercept (equation 4) and slope (equation 5). Next, fixed covariates, which are restricted to vary by individual but not time, can be added to the model at level 2 in order to estimate between-individual differences. Equation 6 shows the addition of a fixed covariate (X_{1i}), which varies by individual but not time, to the unconditional linear growth model (equation 2). This estimates the fixed effect, or average effect, of the covariate on the intercept (Y_{01}) and slope (Y_{11}). Dynamic covariates (Z_{ti}), which vary by individual and time, are added the unconditional linear growth model at level 1 and estimate the amount of individual variation in the effect of the covariate (U_{2i}) accounting for change over time and any fixed covariates included in the model (see equation 7). In other words, it estimates individual differences in the relationship, or slope, between the covariate and violence.

$$\text{Unconditional mean model: } Y_{it} = Y_{00} + Y_{10}TIME_{ti} + e_{ti} \quad (1)$$

$$\text{Unconditional linear growth model:} Y_{it} = Y_{00} + U_{0i} + Y_{10}TIME_{ti} + U_{1i}TIME_{ti} + e_{ti} \quad (2)$$

$$\text{Level 1: } Y_{it} = \boldsymbol{\beta}_{0i} + \boldsymbol{\beta}_{1i}\,TIME_{ti} + e_{ti} \quad (3)$$

$$\text{Level 2: } \boldsymbol{\beta}_{0i} = Y_{00} + U_{0i} \quad (4)$$

$$\text{Level 2: } \boldsymbol{\beta}_{1i} = Y_{10} + U_{1i} \quad (5)$$

$$\text{Fixed covariate added: } Y_{it} = Y_{00} + Y_{01}X_{1i} + U_{0i} + Y_{10}TIME_{ti} + Y_{11}X_{1i} + U_{1i}TIME_{ti} + e_{ti} \quad (6)$$

$$\text{Dynamic covariate added: } Y_{it} = Y_{00} + U_{0i} + Y_{10}TIME_{ti} + U_{1i}TIME_{ti} + U_{2i}Z_{ti} + e_{ti} \quad (7)$$

In this way, both intraindividual and interindividual differences can be examined, as well as both static and dynamic predictors of violence.

Item Response Models allow better interpretation of self-reported violence

One problem with using survey research is the restriction of the outcome variable to an ordinal scale. This leads to ceiling and floor effects in regression (Francis et al., 1994). Additionally, slope estimates do not yield true “rates” of change but identify differences in patterns of change (Francis et al., 2000). Item response modeling (IRM) is one approach, based on item response theory (IRT), which allows the transferring of ordinal scales onto continuous scales (Osgood, McMorris, & Potenza, 2002; Samejima, 1997).

IRM is an innovative approach to scaling violence; Cui (2012) stated that very few studies (Osgood and Anderson 2004; Osgood, Finken, and McMorris 2002; Osgood et al., 2002b; Piquero, MacIntosh, and Hickman 2000) have applied IRM to the study of crime/delinquency. Ordinal or dichotomous items are translated onto a continuous scale by computing a probability score for each response. An important advantage of using IRM includes differential weighting based on the seriousness of the violent offense (Osgood et al., 2002b; Samejima, 1997). For these reasons, the present study incorporated IRM to create a continuous measure of violence.

Method

Overview and design

The current study aims to identify predictors of within-individual change in violent offending among males in a nationally representative longitudinal sample of youth using growth modeling. The publicly available data set includes a subsample from the Add Health study and is limited to Wave 1 and Wave 2. Two waves, or collection points, of data allow the minimum needed to obtain a growth estimate. Self-reported violence was translated onto a continuous scale using IRM. Bivariate Pearson’s correlations were calculated to construct a correlation matrix of all variables in the current study. An unconditional random intercepts model, a type of linear growth model, was estimated. A variance components covariance structure was tested. Demographic control variables, which included race/ethnicity, parent’s highest level of education, and family poverty, were tested as fixed effects and controlled for in all models. Fixed effects were entered into the random intercepts model in chunks, organized by school, mental health, and social factors. Stepwise model selection was used to build a model with significant fixed effects. Paired-sample t-tests estimated within-individual variation on dynamic variables, chosen for their predictive power from previous research and treatability. The dynamic effects of variables showing significant within-individual variability were examined individually while controlling for significant fixed effects. The resulting nested models tested whether dynamic variables predict within-individual change in violence and whether static variables predict violence between individuals.

The purpose of the present study was to (a) identify dynamic variables that relate to within-individual change in youth violence above and beyond fixed effects; (b) examine whether static and control variables predict differences in violence between individuals; and (c) examine the interaction between peer delinquency and age.

The following hypotheses were examined:

H1: Violence will vary significantly within individuals between Wave 1 and 2

H2: On average, violence will increase within individuals over time

H3: Demographic control variables will significantly predict differences in violence between individuals

H4: Dynamic variables, including GPA, peer delinquency, a daily family meal, truancy, school attachment, depressive symptoms, drug use, and alcohol use will significantly predict within-individual change in violence

H5: Low verbal IQ and repeated grade will predict higher levels of violence between individuals above and beyond demographic control variables

H6: Age will interact with peer delinquency.

Data and Sample

Add Health study design. Add Health is a school-based longitudinal study of adolescents in 7th to 12th grade in the United States (www.cpc.unc.edu/addhealth). High schools were randomly selected from a sampling frame stratified by size, region, urbanicity, and percentage white. Selected high schools were matched with their primary feeder school that included 7th grade. There are a total of 132 schools in the study. Of the eligible students in grades 7-12, 90,118 respondents completed an in-school paper-and-pencil survey during the 1994-1995 school year.

A subsample (Wave 1; ages 12-17; n=20,745), stratified by grade and gender, was selected for a 90-minute computer-assisted in-home interview between April and December

1995. Sensitive questions were delivered through earphones and adolescents entered their responses directly onto a laptop computer, a method shown to maximize reporting among adolescents (Turner, Rogers, et al., 1998). All of the Wave 1 participants, excluding the 12th graders, were invited to complete a follow-up survey between April and September 1996 (Wave 2; n=14,738). All Wave 1 participants, including 12th graders, who could be located and interviewed, participated in Wave 3 interviews (Wave 3; ages 18-26; n=15,170) between 2001 and 2002. Ninety two percent of Wave 1 participants were located for a fourth in-home interview and biological specimen collection and 80% participated between 2008 and 2009 (Wave 4; ages 24-32; n=15,701).

Study sample and eligibility criteria. For this study, the sample included males from the publicly available dataset who completed the in-home interviews at Wave 1 and Wave 2. The public dataset includes 3147 males at Wave 1 and 2315 males at Wave 2. Two thousand two hundred eighty eight males reported on their levels of violence at both waves. The average length of time between the two available data points for an individual was 11 months. Sixty nine percent of males endorsed at least one of seven violent acts at Wave 1, while 38% endorsed at least one out of seven violent acts at Wave 2.

Measures

Outcome variable. The dependent variable for this analysis is based on a seven-item scale of self-reported violence, which was adapted from Resnick et al. (1997), assessed at Wave 1 and 2. Once a fierce debate between criminologists, self-reports are considered a reliable and valid method of measuring violence, especially since evidence has shown that official police reports substantially underestimate criminality (Loeber et al., 2008; Thornberry, 2000). The degree of violent offending was measured by computing the probability score for each respondent based on their responses to several different items in the Add Health violence scale using Samejima's (1997) graded response model (GR), a type of IRM which translates ordered responses into probabilities using a logistic function. IRM is based on item response theory (IRT) and models the relationship between a latent trait and item responses. Developing the dependent variable using IRT allows differential weighting based on the seriousness of the violent offense and transfers the survey responses onto a continuous scale with a probability score for each item and respondent (Osgood, McMorris, & Potenza, 2002; Samejima, 1997).

Three item response models were built to model the responses to the following questions: "During the past 12 months how often did you…" (a) *use or threaten to use a weapon to get something from someone?*; (b) *take part in a group fight?*; (c) *get into a serious physical fight?;* (d) *get into a fight where you were injured and had to be treated by a doctor or nurse?*; (e) *hurt someone badly enough to need bandages or care from a doctor or nurse?*; (f) *pull a knife/gun on someone?*; or (g) *shoot/stab someone?* Responses included *never* (0), *once* (1), or *more than once* (2). This scale was found reliable at both waves. Refer to Table 2 for Cronbach's alpha coefficients. The final model included five items (see IRT results).

Demographic control variables. Demographic characteristics, such as race/ethnicity, age, and socioeconomic status (SES), as measured by family poverty and parent education, were controlled for in all models due to evidence of their confounding effects on violent offending **(**Resnick et al., 1997). In addition, the language primarily spoken in the home controlled for consequential differences in Verbal IQ.

Race/ethnicity. Race and ethnicity were assessed during Wave 1 of the in-home interview. The following responses were entered into the model as a single categorical variable: *White* (non-Hispanic), *Hispanic or Latino, Black or African American, American Indian or Native American, Asian or Pacific Islander, or Other*. Dichotomous variables were not examined since differences in violence between ethnicities are out of the scope of the current project. See Cui (2012) for a comprehensive examination of racial differences in predictors of violence.

Age. Age was calculated at each wave by subtracting the interview date from date of birth assessed at Wave 1.

Family poverty. This measure is replicated from Wickrama, Noh, and Elder (2010). During the parent in-home questionnaire at Wave 1, parents were asked whether they or any member of their household received social assistance as measured by six dichotomous items: (a) Social Security or Railroad Retirement, (b) Supplemental Security Income, (c) Aid to Families with Dependent Children, (d) food stamps, (e) unemployment or worker's compensations, or (f) a housing subsidy or public housing. Responses were be coded as *yes* (1) or *no* (0), and the measure equals the sum of responses. Wickrama et al. (2010) found this measure to be internally consistent (KR-20=0.85).

Parent education. This measure is adapted from Wickrama et al. (2010). Parents' highest level of education was measured using two items from the parent in-home questionnaire. The first question asked parents to identify their highest level of education, while the second question asked parents to identify their spouse's highest level of education. Responses included *never went to school* (6), *8th grade or less* (5), *more than 8th grade, but did not graduate from high school* (4), high school graduate or equivalent (3), some college

(2) four year college degree (1), or *professional training beyond a 4-year college or university* (0). Of the two questions, the lowest response was retained.

English not spoken in home. Participants were asked at Wave 1 what language was primarily spoken in their home. Responses were coded as English (0) or Otherwise (1).

Independent variables. This study is based on 10 predictors of youth violence established from previous research in the domains of individual, family, peer, and school factors. Table 2 displays a brief description of each measure, including the number of items, an example question, the answer scale or cutoff, the number of waves included, and the Cronbach's alpha coefficient.

Most of the predictors were measured at Wave 1 and 2, when the participants were in the seventh to 12^{th} grade. Verbal IQ and repeated grade were measured at Wave 1. A more detailed description of each measure, organized according to static and potential dynamic properties, follows.

Dynamic variables.

Grade Point Average (GPA). The mean of four items, which measure self-reported grades in English, Math, History at Waves 1 and 2, determines the youths' academic achievement. Responses included A (4), B (3), C (2), or D or less (1). This scale was found reliable at both waves (see Table 2).

Delinquent peers. This measure, adapted from Guo (2008) and Cui (2012), assesses the adolescent's level of association with peers who commit minor types of delinquency, such as drinking alcohol, smoking cigarettes, and using marijuana. Substance use among peers is used as a proxy for other minor acts of delinquency here. The measure equals the sum of three items asked during Wave 1 and 2, which measured how many of the participants' three best friends engaged in each activity at least once a month. Cui (2012) found that these questions load high on one factor with scores .81 and higher; he also found that the first factor explained 67% of the variance for the latent construct. This scale was found reliable at both waves (see Table 2).

A daily family meal. This variable is replicated from Guo (2008) and is based on a single-item measure assessed during Wave 1 and 2 of the in-home interview: *On how many of the past seven days was at least one of your parents in the room with you while you ate your evening meal?* Answers were coded as follows: 6 or more days=0, otherwise=1.

Truancy. This variable is based on a single-item measure assessed during Wave 1 and 2. Participants were asked: *In the past school year, how many times did you skip school for a full day without an excuse?* Responses were coded on a continuous scale.

School attachment. This measure, adapted from Resnick et al. (2004), is based on the sum of seven items measured during Wave 1 and 2, which assessed how much adolescents' got along with teachers and classmates, felt close to people at school, felt a part of their school, were happy and felt safe at school, and felt that teachers were fair. All items were reverse scored with a higher score indicating a higher school attachment. This scale was found reliable at both waves (see Table 2).

Depressive symptoms. This measure is based on the mean of eight items assessed at Wave 1 and 2. It was adapted from Remster (2013) and quantifies the level of depression experienced by the participant in the past week. A slightly modified version of the Center for Epidemiological Studies Depression Scale (CES-D 10) (Kohout et al., 1993; as cited by Remster, 2013) was used in the ADD Health study. Participants were asked how often they experienced each of the following in the past seven days: (a) *You felt depressed*, (b) *You felt* *that you were too tired to do things*, (c) *You were happy* (reverse scored), (d) *You felt lonely,* (e) *You enjoyed life* (reverse scored), (f) *You felt sad*, (g) *You felt that people disliked you*, and (h) *It was hard to start doing things*. Response options included *never or rarely* (0), *sometimes* (1), *a lot of the time* (2), and *most of the time or all of the time* (3). A higher value on this measure indicates higher levels of depression. This scale was found reliable at both waves (see Table 2).

Drug use. This measure is based on the mean of four items asked during the in-home interview at Waves 1 and 2. Participants were asked the following: (1) *During the past 30 days, how many times have you used marijuana?;* (2) *During the past 30 days, how many times have you used cocaine?;* (3) *During the past 30 days, how many times have you used inhalants?;* (4) *During the past 30 days, how many times have you any other type of illegal drug, such as LSD, PCP, ecstasy, mushrooms, speed, ice, heroin, or pills, without a doctor's prescription?* Responses were continuous, with a larger score on this measure indicating more drug use. This scale was found reliable at both waves (see Table 2).

Alcohol use. This measure is based on a single item asked during the in-home interview at Waves 1 and 2. Participants were asked how many days they got drunk or "very, very high" on alcohol in the past 12 months. Responses included *none* (0), *1 or two days in the past 12 months* (1), *once a month or less* (2), *two or three days a month* (3), *1 or 2 days a week* (4), *3 to 5 days a week* (5), and *every day or almost every day* (6). A larger score on this item indicates more alcohol use.

Static variables.

History of grade retention. This measure is based a single item assessed at Wave 1. Participants were asked whether they had ever repeated a grade or been held back. Participants who endorsed the item received a score of 1; otherwise they were coded as 0.

Verbal IQ. The PVT, a slightly abbreviated version of the Peabody Picture Vocabulary Test (Lubin, Larsen, and Matarazzo 1984; Rice and Brown 1967; as cited by Guo et al., 2008), was given at Wave 1. The PVT is generally regarded as a measure of verbal IQ (Guo et al., 2008). Responses are continuous but were coded to distinguish those individuals who have at least average verbal intelligence (90 or greater)=0, low average verbal intelligence (80 to 89)=1, borderline impaired verbal intelligence (70 to 79)=2, or impaired verbal intelligence (less than 70)=3. Due to likely confounding effects, we controlled for whether English is spoken in the home, which was previously described under demographic control variables.

Data Analysis Strategy

Item Response Modeling.

First, the outcome variable (violent offending) was translated onto a continuous scale using Samejima's (1997) GR model, a type of IRM. The GR model is appropriate when item responses are ordered categorical and items have different response formats (Embretson & Reise, 2000). It is considered an "indirect" IRT model because it requires two steps in order to compute the conditional probability for an examinee responding in a particular category. There are three model assumptions: local independence, monotonicity, and unidimensionality (Rupp, 2003). IRTPRO for Windows, a stand-alone computer software package that assists in the application of IRT modeling, was used to estimate item and person parameters for the GR model (Embretson & Reise, 2000). The subsequent model fit was assessed by the standardized weighted mean squares of the item residuals, which are computed in IRTPRO. The standardized residuals indicate standardized discrepancies, which are weighted as a function of the variances of the expected response probabilities. IRTPRO also calculates tests of item fit, such as the $S\text{-}X^2$ index, and a test of dependence, such as the standardized local dependence index, which is based on the Chen and Thissen (1997) test of local dependence. The factor loadings for each item were examined to identify multidimensionality. Person ability estimates were exported for SPSS.

Repeated Measures ANOVA.

SPSS was used to collate the data into one record per youth, as well as code the measures. Continuous independent variables, including GPA, truancy, school attachment, depressive symptoms, drug use, and alcohol use, were centered to the mean in order to make the intercept more interpretable. An inspection of the skewness and kurtosis measures, visual inspection of histograms, and QQplots indicated that violence was negatively skewed. A constant was added to each observation to account for negatives and zeros and log10 transformations were used to account for non-normality. Visual inspection of histograms and frequency tables were used to identify outliers, which were transformed with winzorization. With only two levels of a repeated measure factor, the assumption of sphericity is always met (Hinton, McMurray, & Brownlow, 2004), so Hartley's test for homogeneity of variance was conducted and results showed borderline acceptance for the assumption.

Since the data is limited to two time points, repeated measures ANOVA was used to determine whether individuals changed significantly between Wave 1 and 2 on the violence measure (Hypothesis 1). The transformed violence variables (Wave 1 & 2) were modeled as a function of time. The significance of the within-individual contrast was examined.

Multilevel Modeling.

Growth modeling, a type of multilevel modeling (MLM), was used to examine correlates of within-individual change (or growth) in violent offending. Growth modeling is able to easily handle unbalanced data, missing data, and uneven time points unlike more traditional approaches to longitudinal data, such as repeated measures ANOVA. MLM assumes homogeneity of error variance and that errors are normally distributed (Raudenbush & Bryk, 2002). Growth modeling is ideal for the examination of dynamic and static variables since it allows for within-individual analyses as well as between-individual analyses. The multilevel models were built using SPSS Mixed.

The Mixed procedure in SPSS was used for multilevel model building. The data was translated from horizontal to vertical format, which is appropriate for the mixed procedure. Since the random slopes model requires at least three data points, this analysis was restricted to a random intercept model, which implies a compound symmetric covariance structure. To account for unequal sampling probabilities, all models were scaled using the most appropriate weight recommended by Add Health's User's Guide for longitudinal analysis: the sampling weight calculated for adolescents interviewed at Wave 1 and 2 for population average models.

An unconditional mean model was built with SPSS mixed in which violence was regressed on time as a fixed factor to estimate the grand mean of violence (fixed intercept) and the estimated population growth rate (fixed time). The parameter estimate of time demonstrated the direction of the average rate of change within individuals (hypothesis 2).

Then an unconditional random intercepts model estimated the average variation from the grand mean of violence. The residual error from this model was compared to other random models to obtain an R-square estimate.

Eleven multilevel models were built to test for fixed and random effects. First, fixed effects were entered into the random intercepts model in chunks, organized by school, mental health, and social factors. Stepwise model selection was used to build a model with the greatest fixed effects. AIC, BIC scores, and the chi-square likelihood test were obtained to assess model fit. Demographic control variables were controlled for in all models.

The following fixed effects were examined sequentially (from Model 1 to 7): demographic control variables, alone (model 1); school/achievement factors, including GPA, school attachment, truancy, history of repeated grade, low verbal IQ, and English not spoken in the home (control variable) (model 2); history of repeated grade, alone (model 3); mental health factors, including depressive symptoms, alcohol use, and drug use (model 4); depressive symptoms, alone (model 5); social factors, including peer delinquency and a daily family meal (model 6); and a combined model, including demographic control variables, history of repeated grade, peer delinquency, and a daily family meal. The fixed effects of all variables, including demographic control variables (hypothesis 3) and static variables, estimated their relations with violent offending between individuals (hypothesis 5). The interaction between peer delinquency and age was tested in model 7, while controlling for demographic variables, history of repeated grade, and a daily family meal (hypothesis 6).

Paired-sample t-tests examined within-individual variation on all dynamic variables. The random effects of dynamic variables showing significant within-individual variability were examined individually while controlling for the following fixed effects: demographic control variables, a history of repeated grade, peer delinquency, and a daily family meal. The following dynamic variables were entered, individually, into the random intercepts model at level-1: peer delinquency, a daily family meal, and alcohol use. Chi-square and Wald Z statistics determined the significance of covariance parameters. R-square estimated the amount of within-individual variance in violence accounted for by each dynamic variable. The covariance parameters of significant dynamic variables estimated the amount of variation in the effect of the predictor on violence after accounting for change over time and any covariates included in the model. This tests whether dynamic predictors covary with within-individual violence (hypothesis 4).

Results

IRT Analysis Results

Three models were tested in IRTPRO for violent offending at Wave 1. In the first model, all seven items were included. After examining the model fit, it was determined that there was poor factor loading for a single item: (d) *get into a fight where you were injured and had to be treated by a doctor or nurse.* In addition, the results indicated poor item fit for the following two items, in addition to item (d): (c) *get into a serious physical fight* and (e) *hurt someone badly enough to need bandages or care from a doctor or nurse.* Large standard residuals indicated poor overall model fit. Item (d) was removed from the model, which resulted in good factor loadings for all items but poor item fit for items (c) and (e). The Chen and Thissen (1997) test of local dependence indicated that items (c) and (e) were too highly correlated. Standard residuals also indicated poor overall model fit. In the third model, item (c) and (e) were combined by creating a new item that equaled the average of the two items. The results showed good factor loadings for all five items, and item level statistics indicated good item fit and local independence. Last, standard residuals were acceptable, indicating good overall model fit. Table 3 compares the factor loadings for model 1 and model 3. Table 4 presents the item parameter estimates for the final model (model 3).

Descriptive Statistics

The descriptive statistics for all variables prior to centering continuous variables are presented in Table 5. Regarding demographic characteristics of the sample, whites accounted for the largest proportion of the sample (60%), followed by blacks (24%), Latinos (6%), Asians (4%), Native American (3%), and other (3%). The average age at Wave 1 was 16, while the average age at Wave 2 was 17. About seven percent of the sample lived in a household where the primary language was not English.

Repeated Measures ANOVA Results

Repeated Measures ANOVA was used to test whether individuals changed in level of reported violence from Wave 1 to 2 (hypothesis 1). Self-reported violence was modeled as a function of time. A significant within-subjects contrast ($F=42.25$, $p<0.001$) confirmed that violence varied on average from Wave 1 to Wave 2 within-individuals.

Paired-Sample T-tests Results

Paired-sample t-tests examined within-individual variation on all dynamic variables. Mean within-individual differences are presented in Table 6. The results indicated that peer delinquency, a daily family meal, and alcohol use significantly changed within individuals from Wave 1 to 2, demonstrating their malleability. Within-individual differences in GPA, school attachment, truancy, drug use, and depressive symptoms failed to reach significance. Random effects of peer delinquency, a daily family meal, and alcohol use were estimated to confirm significant covariation with violence.

Multilevel Modeling Results

Eleven multilevel models were built to estimate the relations between transformed individual probability estimates of violence obtained from IRTPRO with fixed and dynamic variables. R-squared values for dynamic variables, which estimate the proportion of within-individual variance in violence that is explained by the model, were calculated by comparing error covariance estimates to the unconditional random intercepts model. Table 7 displays the correlation matrix of all variables in the study. All correlation coefficients were less than 0.4. The strongest correlation was between depressive symptoms and school attachment ($r=0.36$, $p<.001$). Results of the 11 models for violent offending are presented in Table 8.

The parameter estimate for the fixed effect of the intercept ($b=1.74$, $p<0.001$) in the unconditional mean model, or fixed model, estimates the population mean for violence based on the IRT scale developed for the study. The fixed effect of time ($b=-0.31$, $p<0.001$) in the null model estimates the average growth rate in violence. Contrary to hypothesis 2, this shows that individuals decreased in violence on average across the two time points (hypothesis 2). Model 1 examines the relationship between demographic control variables and violent offending. Race ($b=0.1$, $p<0.01$), family poverty ($b=0.15$, $p<0.001$), and parent’s highest level of education ($b=0.08$, $p<0.01$) were all significantly related to violent offending. Since race was included as a control variable and contrasts between races were not planned or of interest, a dummy variable was used. This controls for differences in race in the model. Recall that parent’s highest level of education was reverse-coded, meaning a higher score indicates a lower level of education. The results suggest that violent offending increases between individuals as parent’s education decreases and family poverty increases.

Demographic control variables accounted for 21% of the between-individual variance in violent offending.

Model 2 examines the relationship between school factors and violent offending, while controlling for demographic control variables. Individuals with a higher GPA ($b=-0.21$, $p<0.001$) and greater school attachment ($b=-0.07$, $p<0.001$) reported less violence, while individuals who were more truant ($b=0.03$, $p<0.001$) and had a history of grade retention ($b=0.19$, $p<0.001$) reported more violence. Having a low verbal IQ did not predict differences in self-reported violence across individuals ($b=0.08$, $p>0.05$). Model 2 explained 18% of the variance in violence between individuals. History of grade retention was examined individually in model 3, while controlling for demographic variables. The fixed effect of grade retention increased ($b=0.36$, $p<0.001$), and the variance explained increased to 24%.

The fixed effects of mental health variables, including depressive symptoms, alcohol use, and drug use, were examined in model 4. The results show significant effects of depressive symptoms ($b=0.37$, $p<0.01$), drug use ($b=0.01$, $p<0.001$), and alcohol use ($b=0.25$, $p<0.01$) on self-reported violence. However, the amount of variance explained by the model equaled zero, so the effects may be very small and should be interpreted with caution. Model 5 estimated the fixed effect of depressive symptoms, individually, while controlling for demographic variables. Individuals who reported more depressive symptoms reported a higher level of violence ($b=0.60$, $p<0.001$). Model 5 accounted for 9% of the variance in violence between individuals. Compared to model 5, demographic control variables alone in model 1 accounted for much more variance (R-square=0.21).

Model 6 estimated the fixed effects of peer delinquency and a daily family meal while controlling for demographic variables. The results showed a positive relationship between peer delinquency and violence ($b=0.18$, $p<0.001$). In addition, individuals who had a daily family meal (reverse-coded) reported less violence compared to those who do not ($b=0.15$, $p<0.01$). R-square indicated that model 6 accounted for 49% of the variance in between-individual violence.

Model 7 combined the fixed effects of model 3 and 6 to obtain estimates for history of grade retention ($b=0.32$, $p<0.001$), peer delinquency ($b=0.18$, $p<0.001$), and a daily family meal ($b=0.17$, $p<0.001$), while controlling for demographic variables. The total between-individual variance accounted for by this model equaled 58%.

Model 8 examined the interaction between peer delinquency and age (hypothesis 6). The interaction between peer delinquency and age did not significantly predict the level of violence between individuals above the fixed effects in model 7 ($b=-0.006$, $p>0.05$). We cannot conclude that the effect of peer delinquency on violence between individuals changes with age.

Models 9, 10, and 11 examined the random effects of peer delinquency, a daily family meal, and alcohol use, individually, over the fixed effects included in model 7. Alcohol use was added as a fixed effect in model 11, which examines its random effect. In model 9, peer delinquency significantly covaried with within-individual violence (variance component=0.03, $p<0.001$). Therefore, a change in peer delinquency related to a change in violence. Peer delinquency accounted for 5% of the variance in within-individual violence. Model 10 showed that a daily family meal (variance component=0.43, $p<0.001$) demonstrated a significant dynamic effect on within-individual violence and accounted for

3% of the within-individual variance in violence. Last, alcohol use demonstrated a significant dynamic effect on within-individual violence (variance component=0.11, $p<0.001$), however, the R-square was equal to zero. This effect may be miniscule and should be interpreted with caution. We can conclude that peer delinquency and having a daily family meal exhibit dynamic effects on within-individual violence.

Discussion

Repeated measures ANOVA indicated that violence varied significantly within individuals between Wave 1 and 2 (hypothesis 1). Contrary to hypothesis 2, the multilevel models indicated that violence decreased with age, on average, both within and between individuals. Demographic control variables significantly predicted violence between individuals (hypothesis 3). A daily family meal, peer delinquency, and alcohol use varied significantly within-individuals between measurement points and covaried with within-individual change in violence while controlling for fixed covariates (hypothesis 4). Since GPA, school attachment, truancy, drug use, and depressive symptoms did not show significant within-individual variation, their dynamic effects could not be estimated. The following variables predicted the level of violence between individuals: age, race, family poverty, parent education, GPA, school attachment, history of grade retention, depressive symptoms, peer delinquency, and a daily family meal. Overall, school and mental health factors did not account for much variance in violence over demographic control variables. Demographic control variables, history of grade retention, peer delinquency, and a daily family meal accounted for the greatest amount of variance in violence between individuals (R-square=0.51). The addition of peer delinquency at level-1 over these fixed effects accounted for 58% of between-individual variance, and 5% of within-individual variance.

The results of the multilevel models are promising for risk management since association with delinquent peers and a daily family meal, which is a proxy for parental supervision, can be monitored and managed. Overall, peer delinquency demonstrated the greatest dynamic effect and fixed effect, in combination with a daily family meal, on youth violence. This finding is not surprising, given conclusions by other researchers that delinquent peers are one of the strongest and most consistent predictors of youth violence (Loeber et al., 2008). The mean growth estimate in the current study was negative, meaning that the majority of youth decrease in propensity for violence with age, which supports Moffitt's theory of adolescent delinquency. Future research should apply multilevel modeling, or mixed modeling, to the study of dynamic variables in the prediction of different life-course trajectories of violence, such as adolescent-limited and life-course persistent offenders.

Our results show preliminary support for parental supervision as a dynamic variable. Although parental supervision was not directly measured in this study, a daily family meal served as a proxy. Our results are congruent with Guo et al. (2008). Parents who were present during the participant's evening meal on at least six days a week protected youth against violence, while parents who were not present put youth at risk of violent offending. Some researchers have suggested that parental supervision exhibits effects on youth violence through its effect on peer delinquency. However, peer delinquency and a daily family meal were not highly correlated at level 1 ($r=0.19$). The results of this analysis suggest that a daily family meal has an independent and dynamic effect on youth violence.

Depressive symptoms, alcohol use and drug use are frequently named as correlates of youth and adult violence, however, the results of this analysis failed to find evidence of dynamic effects for depressive symptoms or drug use. While individuals who reported higher levels of depression and drug use reported more violent offending, a relationship with within-individual violence could not be ascertained given the lack of variability within individuals. In addition, these effects did not account for much variance in violence between or, in the case of alcohol use, within individuals.

Implications for violence research include the benefit of using modern data analysis procedures to re-analyze preexisting longitudinal datasets. Item response modeling for the dependent measure can have important effects on outcomes and conclusions. In addition, the exploration of dynamic variables using multilevel modeling can identify potential targets for treatment. Age should be considered when evaluating predictors of violence due to the changing effects across development. Examining the interaction effects between predictors and age has implications for both risk assessment and intervention.

Limitations

A few limitations must be noted. Add Health is a school-based sample, so the findings may not generalize to youth who have dropped out of school and likely have a higher rate of violence. For instance, approximately 12 participants from the sibling sample, who were interviewed at Wave 1 and 2, were not interviewed at Wave 3 because they were incarcerated. Additionally, predictors are limited to those that can be reliably assessed by the in-home interview. Secondary analyses are always limited in the range of predictive variables that can be studied. While the current study used the maximum number of time points available in the Add Health public dataset, studies with two time points are vulnerable to measurement error; as Lord stated, “differences between scores tend to be much more unreliable than the scores themselves” (1956, p. 429; as cited in Rogosa, 1988). Three data points is the minimum necessary for a quadratic growth estimate. Although Add Health used computer survey methods shown to maximize reporting among adolescents (Turner, Rogers, et al., 1998), self-report measures are susceptible to invalid responding. On the other hand, self-reported violence is a valid and reliable measure of violence; the Pittsburgh Youth Study (PYS) showed that youth reported higher rates of serious offending than was obtained by arrest records (Loeber et al., 2008). The results should not be taken as an exhaustive list of the predictors of change in violence but as a preliminary analysis on which future analyses of longitudinal designs can expand upon.

References

Bannon, M. J., & Whitty, C. J. (1995). Neurokinin receptor gene expression in substantia nigra: localization, regulation, and potential physiological significance. *Canadian journal of physiology and pharmacology*, *73*(7), 866-870.

Beaver, K. M., Wright, J. P., DeLisi, M., Walsh, A., Vaughn, M. G., Boisvert, D., & Vaske, J. (2007). A gene× gene interaction between DRD2 and DRD4 is associated with conduct disorder and antisocial behavior in males. Behav Brain Funct, 3(30.10), 1186.

Benda, B., Corwyn, R.F., & Toombs, N.J. (2001). Prediction of entry into the correctional system for adults. Criminal Justice and Behavior, 28, 5: 588-613.

Bernat, D. H., Oakes, J. M., Pettingell, S. L., & Resnick, M. (2012). Risk and direct protective factors for youth violence: results from the National Longitudinal Study of Adolescent Health. *American journal of preventive medicine*, *43*(2), S57-S66.

Beyers, J. M., Loeber, R., Wikström, P. H., & Stouthamer-Loeber, M. (2001). What predicts adolescent violence in better-off neighborhoods?*Journal of Abnormal Child Psychology*, *29*, 369– 381.

Boutwell, B. B., & Beaver, K. M. (2008). A biosocial explanation of delinquency abstention. *Criminal Behaviour and Mental Health*, *18*(1), 59-74.

Brook, D. W., Brook, J. S., Rubenstone, E., Zhang, C., & Saar, N. S. (2011). Developmental associations between externalizing behaviors, peer delinquency, drug use, perceived neighborhood crime, and violent behavior in urban communities. *Aggressive behavior*, *37*(4), 349-361.

Brunner, H. G., Nelen, M., Breakefield, X. O., Ropers, H. H., & Van Oost, B. A. (1993). Abnormal behavior associated with a point mutation in the structural gene for monoamine oxidase A. *Science*, *262*(5133), 578-580.

Bryk, A. S., & Raudenbush, S. W. Hierarchical linear models: Applications and data analysis methods, 1992.

Cases, O., Seif, I., Grimsby, J., Gaspar, P., Chen, K., Pournin, S., ... & De Maeyer, E. (1995). Aggressive behavior and altered amounts of brain serotonin and norepinephrine in mice lacking MAOA. *Science (New York, NY)*, *268*(5218), 1763.

Caspi, A., McClay, J., Moffitt, T. E., Mill, J., Martin, J., Craig, I. W., ... & Poulton, R. (2002). Role of genotype in the cycle of violence in maltreated children. Science, 297(5582), 851-854.

Centers for Disease Control and Prevention, National Center for Injury Prevention and Control. Web-based Injury Statistics Query and Reporting System (WISQARS) [online]. (2010). [cited 2014 July 10] Available from www.cdc.gov/injury.

Cook Jr, E. H., Stein, M. A., Krasowski, M. D., Cox, N. J., Olkon, D. M., Kieffer, J. E., & Leventhal, B. L. (1995). Association of attention-deficit disorder and the dopamine transporter gene. *American journal of human genetics*, *56*(4), 993.

Cohen, M. A., & Piquero, A. R. (2008). New Evidence on the Monetary Value of Saving a High Risk Youth.Cornish, K. M., Manly, T., Savage, R., Swanson, J., Morisano, D., Butler, N., ... & Hollis, C. P. (2005). Association of the dopamine transporter (DAT1) 10/10-repeat genotype with ADHD symptoms and response inhibition in a general population sample. *Molecular psychiatry*, *10*(7), 686-698.

Côté, S. M., Vaillancourt, T., LeBlanc, J. C., Nagin, D. S., & Tremblay, R. E. (2006). The development of physical aggression from toddlerhood to pre-adolescence: A nationwide longitudinal study of Canadian children. *Journal of Abnormal Child Psychology, 34*, 71– 85.

Cottle, C. C., Lee, R. J., & Heilbrun, K. (2001). The prediction of criminal recidivism in juveniles: A meta-analysis. *Criminal Justice and Behavior, 28* (3): 367-394.

Cui, W. (2012). The effect of race on crime: A multilevel analysis. PhD diss., University of Tennessee. Retrieved from: http://trace.tennessee.edu/utk_graddiss/1286 http://trace.tennessee.edu/utk_graddiss/1286

Daigle, L. E. (2010). Risk Heterogeneity and Recurrent Violent Victimization: The Role of DRD4. Biodemography & Social Biology, 56(2), 137-149. doi:10.1080/19485565.2010.524095

Daly, G., Hawi, Z., Fitzgerald, M., & Gill, M. (1999). Mapping susceptibility loci in attention deficit hyperactivity disorder: preferential transmission of parental alleles at DAT1, DBH and DRD5 to
affected children. *Molecular psychiatry*,*4*(2), 192-196.

Deater–Deckard, K. I. R. B. Y., Dodge, K. A., Bates, J. E., & Pettit, G. S. (1998). Multiple risk factors in the development of externalizing behavior problems: Group and individual differences. *Development and psychopathology*, *10*(03), 469-493.

Dishion, T. J., & McMahon, R. J. (1998). Parental monitoring and the prevention of child and adolescent problem behavior: A conceptual and empirical formulation. *Clinical child and family psychology review*, *1*(1), 61-75.

Dodge, K. A., Greenberg, M. T., & Malone, P. S. (2008). Testing an idealized dynamic cascade model of the development of serious violence in adolescence. *Child development*, *79*(6), 1907-1927.

Eamon, M. K., & Mulder, C. (2005). Predicting antisocial behavior among latino young adolescents: an ecological systems analysis. *American Journal of Orthopsychiatry*, *75*(1), 117.

Ellickson, P. (2000). Early predictors of adolescent violence. *American Journal of Public Health*, (4), 566.

Embretson, S. E., & Reise, S. P. (2000). *Item response theory for psychologists*. Psychology Press.

Estrada-Martínez, L. M., Caldwell, C. H., Schulz, A. J., Diez-Roux, A. V., & Pedraza, S. (2011). Families, Neighborhood Socio-Demographic Factors, and Violent Behaviors among Latino, White, and Black Adolescents. *Youth & Society*, 0044118X11411933.

Fergusson, D. M., Boden, J. M., Horwood, L. J., Miller, A. L., & Kennedy, M. A. (2011). MAOA, abuse exposure and antisocial behaviour: 30-year longitudinal study. The British Journal of Psychiatry, 198(6), 457-463.

Francis, D. J., Schatschneider, C., & Carlson, C. D. (2000). Introduction to individual growth curve analysis. In Handbook of research in pediatric and clinical child psychology (pp. 51-73). Springer US.

Francis, D. J., Shaywitz, S. E., Stuebing, K. K., Shaywitz, B. A., & Fletcher, J. M. (1994). The measurement of change: Assessing behavior over time and within a developmental context.

Gill, M., Daly, G., Heron, S., Hawi, Z., & Fitzgerald, M. (1997). Confirmation of association between attention deficit hyperactivity disorder and a dopamine transporter polymorphism. *Molecular psychiatry*, *2*(4), 311-313.

Guo, G., Ou, X. M., Roettger, M., & Shih, J. C. (2008). The VNTR 2 repeat in MAOA and delinquent behavior in adolescence and young adulthood: associations and MAOA promoter activity. European Journal of Human Genetics, 16(5), 626-634.

Guo, G., Roettger, M. E., & Shih, J. C. (2007). Contributions of the DAT1 and DRD2 genes to serious and violent delinquency among adolescents and young adults. Human genetics, 121(1), 125-136.

Heinz, A., Goldman, D., Jones, D. W., Palmour, R., Hommer, D., Gorey, J. G., ... & Weinberger, D. R. (2000). Genotype influences in vivo dopamine transporter availability in human striatum. *Neuropsychopharmacology*, *22*(2), 133-139.

Herrenkohl, T. I., Hill, K. G., Chung, I. J., Guo, J., Abbott, R. D., & Hawkins, J. D. (2003). Protective factors against serious violent behavior in adolescence: A prospective study of aggressive children. *Social Work Research*, *27*(3), 179-191.

Herrenkohl, T. I., Lee, J., & Hawkins, J. D. (2012). Risk versus direct protective factors and youth violence: Seattle Social Development Project.*American journal of preventive medicine*, *43*(2), S41-S56.

Herrenkohl, T. I., Maguin, E., Hill, K. G., Hawkins, J. D., Abbott, R. D., & Catalano, R. F. (2000). Developmental risk factors for youth violence. *Journal of Adolescent Health*, *26*(3), 176-186.

Jacobsen, L. K., Staley, J. K., Zoghbi, S. S., Seibyl, J. P., Kosten, T. R., Innis, R. B., & Gelernter, J. (2000). Prediction of dopamine transporter binding availability by genotype: a preliminary report. *American Journal of Psychiatry*,*157*(10), 1700-1703.

Jennings, W. G., Maldonado-Molina, M. M., & Komro, K. A. (2010). Sex similarities/differences in trajectories of delinquency among urban Chicago youth: The

role of delinquent peers. *American Journal of Criminal Justice*, *35*(1-2), 56-75.

Johnson, S. B., Blum, R. W., & Giedd, J. N. (2009). Adolescent maturity and the brain: the promise and pitfalls of neuroscience research in adolescent health policy. *Journal of Adolescent Health*, *45*(3), 216-221.

Katsiyannis, A., Ryan, J. B., Zhang, D., & Spann, A. (2008). Juvenile delinquency and recidivism: The impact of academic achievement. *Reading & Writing Quarterly*, *24*(2), 177-196.

Kim-Cohen, J. J., Caspi, A. A., Taylor, A. A., Williams, B. B., Newcombe, R. R., Craig, I. W., & Moffitt, T. E. (2006). MAOA, maltreatment, and gene–environment interaction predicting children's mental health: new evidence and a meta-analysis. Molecular Psychiatry, 11(10), 903-913.

Kim, S., Orpinas, P., Kamphaus, R., & Kelder, S. H. (2011). A multiple risk factors model of the development of aggression among early adolescents from urban disadvantaged neighborhoods. School Psychology Quarterly, 26(3), 215-230. doi:10.1037/a0024116

Knoester, C., & Haynie, D. L. (2005). Community context, social integration into family, and youth violence. *Journal of Marriage and Family*, *67*(3), 767-780.

Kraemer, H. C., Kazdin, A. E., Offord, D. R., Kessler, R. C., Jensen, P. S., & Kupfer, D. J. (1997). Coming to terms with the terms of risk. *Archives of general psychiatry*, *54*(4), 337-343.

Kroner, D. G., & Yessine, A. K. (2013). Changing risk factors that impact recidivism: In search of mechanisms of change.

Laird, R. D., Pettit, G. S., Bates, J. E., & Dodge, K. A. (2003). Parents' Monitoring-Relevant Knowledge and Adolescents' Delinquent Behavior: Evidence of Correlated Developmental Changes and Reciprocal Influences.*Child development*, *74*(3), 752-768.

Lansford, J. E., Dodge, K. A., Pettit, G. S., Bates, J. E., Crozier, J., & Kaplow, J. (2002). A 12-year prospective study of the long-term effects of early child physical maltreatment on psychological, behavioral, and academic problems in adolescence. *Archives of Pediatrics & Adolescent Medicine*, *156*(8), 824-830.

Lauritsen, J., & Rezey, M. (2010). *Measuring the prevalence of crime with the national crime victimization survey*. Retrieved from http://www.bjs.gov/ http://www.bjs.gov/

Li, J. J., & Lee, S. S. (2012). Interaction of dopamine transporter (DAT1) genotype and maltreatment for ADHD: a latent class analysis. *Journal of Child Psychology and Psychiatry*, *53*(9), 997-1005.

Loeber, R., Burke, J. D., & Pardini, D. A. (2009). Development and etiology of disruptive and delinquent behavior. *Annual Review of Clinical Psychology*, *5*, 291-310.

Loeber, R., & Farrington, D. P. (2012). Advancing knowledge about direct protective factors that may reduce youth violence. *American journal of preventive medicine*, *43*(2), S24-S27.

Loeber, R., Farrington, D., Stouthamer-Loeber, M., & White, H. R. (2008). Violence and serious theft: development and prediction from childhood to adulthood. New York: Routledge.

Loeber, R., & Pardini, D. (2008). Neurobiology and the development of violence: common assumptions and controversies. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1503), 2491-2503.

Loeber, R., Pardini, D., Homish, D., Wei, E. H., Crawford, A. M., Farrington, D. P., & ... Rosenfeld, R. (2005). The Prediction of Violence and Homicide in Young Men. *Journal Of Consulting And Clinical Psychology*, *73*(6), 1074-1088. doi:10.1037/0022-006X.73.6.1074

López Turley, R. N., Desmond, M., & Bruch, S. K. (2010). Unanticipated Educational Consequences of a Positive Parent-Child Relationship. *Journal of Marriage and Family*, *72*(5), 1377-1390.

Lord, F. M. (1956). The measurement of growth. *Educational and psychological measurement*, *16*(4), 421-437.

Lösel, F., & Farrington, D. P. (2012). Direct protective and buffering protective factors in the development of youth violence. *American Journal of Preventive Medicine*, *43*(2), S8-S23.

Maldonado-Molina, M. M., Reingle, J. M., & Jennings, W. G. (2010). Does alcohol use predict violent behaviors? The relationship between alcohol use and violence in a nationally representative longitudinal sample. *Youth violence and juvenile justice*, 1541204010384492.

Maxwell, S. E., & Delaney, H. D. (2004). *Designing experiments and analyzing data: A model comparison perspective* (Vol. 1). Psychology Press.

McNulty, T. L., Bellair, P. E., & Watts, S. J. (2012). Neighborhood Disadvantage and Verbal Ability as Explanations of the Black–White Difference in Adolescent Violence: Toward an Integrated Model. *Crime & Delinquency*, 0011128712461472.

Moffitt, T. E. (1993). Adolescence-limited and life-course-persistent antisocial behavior: a developmental taxonomy. *Psychological review, 100*(4), 674.

Moffitt, T. E. (1997). Adolescence-limited and life-course persistent offending: A complementary pair of developmental theories. In T. P. Thornberry (Ed.), Developmental theories of crime and delinquency. New Brunswick, NJ: Transaction Publishers.

Moffitt, T. E., & Caspi, A. (2001). Childhood predictors differentiate life-course persistent and adolescence-limited antisocial pathways among males and females. *Development and psychopathology*, *13*(02), 355-375.

Mulder, E., Vermunt, J., Brand, E., Bullens, R., & Van Marle, H. (2012). Recidivism in subgroups of serious juvenile offenders: Different profiles, different risks?. Criminal Behaviour and Mental Health 22: 122–135

Murray, J., Farrington, D. P., & Eisner, M. P. (2009). Drawing conclusions about causes from systematic reviews of risk factors: The Cambridge Quality Checklists. *Journal of Experimental Criminology*, *5*(1), 1-23.

NICHD Early Child Research Network. (2004). Trajectories of physical aggression from toddlerhood to middle childhood. *Monographs of the Society for Research in Child Development.*Serial No. 278, *Vol. 69*, 4.

Noble, E. P., Blum, K., Ritchie, T., Montgomery, A., & Sheridan, P. J. (1991). Allelic association of the D2 dopamine receptor gene with receptor-binding characteristics in alcoholism or gene ism. *Archives of general psychiatry*,*48*(7), 648-654.

Osgood, D.W. and A.L. Anderson. 2004. "Unstructured socializing and rates of delinquency."
Criminology 42:519-550.

Osgood, D.W., L.L. Finken, and B.J. McMorris. 2002. "Analyzing multiple-item measures of crime and deviance II: Tobit regression analysis of transformed scores." Journal of Quantitative Criminology 18:319-347.

Osgood, D.W., B.J. McMorris, and M.T. Potenza. 2002. "Analyzing multiple-item measures of crime and deviance I: Item response theory scaling." Journal of Quantitative Criminology 18:267-296.

Pardini, D. A., Loeber, R., Farrington, D. P., & Stouthamer–Loeber, M. (2012). Identifying direct protective factors for nonviolence. *American journal of preventive medicine*, *43*(2), S28-S40.

Patterson, G. R., Reid, J. B., & Dishion, T. J. (1992). A social learning approach: Vol. 4. Antisocial boys. *Eugene, OR: Castalia*.

Piquero, A. R., MacIntosh, R., & Hickman, M. (2000). Does self-control affect survey response? Applying exploratory, confirmatory, and item response theory analysis to Grasmick et al.'s self-control scale. *Criminology*, *38*(3), 897-930.

Piquero, A. R., Brame, R., Fagan, J., & Moffitt, T. E. (2006). Assessing the offending activity of criminal domestic violence suspects: Offense specialization, escalation, and de-escalation evidence from the spouse assault replication program. Public Health Reports, 4, 409-418.

Raine, A., Moffitt, T. E., Caspi, A., Loeber, R., Stouthamer-Loeber, M., & Lynam, D. (2005). Neurocognitive impairments in boys on the life-course persistent antisocial path. Journal of abnormal psychology, 114(1), 38.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Sage.

Reingle, J. M., Jennings, W. G., Lynne-Landsman, S. D., Cottler, L. B., & Maldonado-Molina, M. M. (2013). Toward an understanding of risk and protective factors for violence among adolescent boys and men: a longitudinal analysis. *Journal of Adolescent Health*, *52*(4), 493-498.

Reingle, J. M., Jennings, W. G., & Maldonado-Molina, M. M. (2011). The mediated effect of contextual risk factors on trajectories of violence: Results from a nationally representative, longitudinal sample of Hispanic adolescents.*American Journal of Criminal Justice*, *36*(4), 327-343.

Rennie, C. E., & Dolan, M. C. (2010). The significance of protective factors in the assessment of risk. *Criminal Behaviour and Mental Health*, *20*(1), 8-22.

Resnick, M. D., Bearman, P. S., Blum, R. W., Bauman, K. E., Harris, K. M., Jones, J., ... & Udry, J. R. (1997). Protecting adolescents from harm: findings from the National Longitudinal Study on Adolescent Health. *Jama*, *278*(10), 823-832.

Resnick, M. D., Ireland, M., & Borowsky, I. (2004). Youth violence perpetration: what protects? What predicts? Findings from the National Longitudinal Study of Adolescent Health. *Journal of adolescent health*, *35*(5), 424-e1.

Ribeaud, D., & Eisner, M. (2010). Risk factors for aggression in pre-adolescence: Risk domains, cumulative risk and gender differences-Results from a prospective longitudinal study in a multi-ethnic urban sample. *European Journal of Criminology*, *7*(6), 460-498.

Rice, J. A., & Brown, L. F. (1967). Validity of the Peabody Picture Vocabulary test in a sample of low IQ children. *American journal of mental deficiency*,*71*(4), 602.

Richards, T. N., Jennings, W. G., Tomsich, E. A., & Gover, A. R. (2012). A longitudinal examination of offending and specialization among a sample of Massachusetts domestic violence offenders. *Journal of interpersonal violence*, 0886260512455519.

Rocque, M., Bierie, D. M., Posick, C., & MacKenzie, D. L. (2013). Unraveling change: Social bonds and recidivism among released offenders. Victims & Offenders, 8(2), 209-230.

Rogosa, D. (1988). Myths about longitudinal research. In *This chapter is a revised version of a colloquium of the same title presented at National Institutes of Health, Stanford University, University of California-Berkeley, Center for Advanced Studies in the Behavioral Sciences, and Vanderbilt University.*. Springer Publishing Co.

Rutter, M. (1985). Resilience in the face of adversity. *British journal of psychiatry*, *147*(1), 598-611.

Rutter M, Tizard J, Whitemore K. (1970). Health, Education, and Behavior. London: Longman

Samejima, F. 1997. "Graded response model." Handbook of modern item response theory:85-100.

Shek, D. T., & Ma, C. (2011). Longitudinal data analyses using linear mixed models in SPSS: concepts, procedures and illustrations. *The Scientific World Journal*, *11*, 42-76.

Shih, J. C., & Thompson, R. F. (1999). Monoamine oxidase in neuropsychiatry and behavior. *American journal of human genetics*, *65*(3), 593.

Sowell, E. R., Thompson, P. M., Holmes, C. J., Jernigan, T. L., & Toga, A. W. (1999). In vivo evidence for post-adolescent brain maturation in frontal and striatal regions. *Nature neuroscience*, *2*(10), 859-861.

Stattin, H., & Kerr, M. (2000). Parental monitoring: A reinterpretation. *Child development*, *71*(4), 1072-1085.

Stouthamer-Loeber, M., Loeber, R., Stallings, R., & Lacourse, E. (2008). Desistance from and Persistence in Offending. *Violence and serious theft; Development and prediction from childhood to adulthood* (). New York City: Routledge.

Thornberry TP, Krohn MD: The Self-Report Method for Measuring Delinquency and Crime: Criminal Justice 2000. Washington, DC: National Institute of Justice, 2000, Vol 4, pp 33– 83.

Turner, C. F., Ku, L., Rogers, S. M., Lindberg, L. D., Pleck, J. H., & Sonenstein, F. L. (1998).

Adolescent sexual behavior, drug use, and violence: increased reporting with computer survey technology. *Science*, *280*(5365), 867-873.

Vaske, J., Wright, J. P., & Beaver, K. M. (2010). A dopamine gene (DRD2) distinguishes between offenders who have and have not been violently victimized. International journal of offender therapy and comparative criminology.

Walker, K., Bowen, E., and Brown, S. (2013). Psychological and criminological factors associated with desistance from violence: A review of the literature. *Aggression and Violent Behavior* 18.2 (2013): 286-299.

Waldman, I. D., Rowe, D. C., Abramowitz, A., Kozel, S. T., Mohr, J. H., Sherman, S. L., Cleveland, H. H., Sanders, M. L., Card, J. H. C., and Stever, C. (1998). Association and linkage of the dopamine transporter tene and attention-deficit hyperactivity disorder in children: Heterogeneity owing to diagnostic subtype and severity. American Journal of Human Genetics 63:1767–76.

Wickrama, K. A. S., Noh, S., & Elder, G. H. (2009). An investigation of family SES-based inequalities in depressive symptoms from early adolescence to emerging adulthood. *Advances in life course research*, *14*(4), 147-161.

Williams , D. (1996). Project LEAD builds bridges . *Corrections Today* , 58 (5), 80-83.

Winzer-Serhan, U. H. (2007). Long-term consequences of maternal smoking and developmental chronic nicotine exposure. Frontiers in bioscience: a journal and virtual library, 13, 636-649.

Yonai, S., Levine, S. Z., & Glicksohn, J. (2013). A national population based examination of the association between age-versatility trajectories and recidivism rates. *Journal of Criminal Justice*, *41*(6), 467-476.

Appendix

Table 1

List of Independent Variables

"Dynamic" variables	Static variables
GPA	Repeated a grade
Delinquent peers	Verbal IQ
Daily family meals	English not spoken in home*
Truancy	Race/ethnicity*
School attachment	Parent education*
Depressive symptoms	Family poverty*
Drug use	
Alcohol use	

Note. *=Demographic variable

Table 2

Description of Variables

Variable Name	Instrument	Waves	No. of items	Example question	Answer scale or cutoff	Cronbach's alpha	Model
Self-reported violence (Y)	Delinquency Scale; Fighting and Violence Questionnaire	1 & 2	7	During the past 12 months how often did you...get into a serious physical fight?	Never, 1-2 times, 3-4 times, 5 or more times	W1=0.74, W2=0.72	level-1 and level-2
GPA (Y)	Academics and Education Questionnaire	1 & 2	4	At the most recent grading period, what was your grade in Math?	A (4), B (3), C (2), or D or lower (4)	W1=0.71, W2=0.74	level-1
Peer delinquency (Y) Guo et al., 2008 Cui, 2012	Tobacco, Alcohol, Drugs Questionnaire	1 & 2	3	Of your 3 best friends, how many use marijuana at least once a month?	0, 1, 2, or 3	W1=0.75, W2=0.74	level-1
Daily family meals (Y), Guo et al., 2008	Relations with Parents Questionnaire	1 & 2	1	On how many of the past seven days was at least one of your parents in the room with you while you ate your evening meal?	6 or more days (1); otherwise (0)	N/A	level-1
Truancy (Y)	Academics and Education questionaire	1 & 2	1	In the past school year, how many times did you skip school for a full day without an excuse?	Continuous	N/A	level-1
School attachment (Y), Resnick et al., 2004	Academics and Education questionaire	1 & 2	7	How much do you… feel close to people at your school?	5-point Likert scale	W1=0.77, W2=0.77	level-1
Depressive symptoms (Y), Remster, 2013	Feelings Scale	1 & 2	8	In the past seven days, how often did you...feel depressed?	never or rarely (0), sometimes (1), a lot of the time (2), or most of the time or all of the time (3)	W1=0.79, W2=0.77	level-1
Drug use (Y)	Tobacco, Alcohol, Drugs Questionnaire	1 & 2	4	During the past 30 days, how many times have you used cocaine?	continuous	W1=0.71, W2=0.99	level-1
Alcohol use (Y)	Tobacco, Alcohol, Drugs Questionnaire	1 & 2	1	Over the past 12 months, on how many days have you gotten drunk?	None (0), 1-2 days (1), once a month (2), 2-3 days/month (3), 1-2 days/week (4), 3-5 days/week (5), every day or almost every day (6)	N/A	level-1

Table 2
(continued)

Family Poverty* (P)	Parent In-home Questionnaire	1	5	Last month, did you or any member of your household receive Social Security?	Yes (1) or no (0)	KR-20=0.85	level-1 and level-2
Parent Education* (P)	Parent In-home Questionnaire	1	1	How far did you (or your current spouse) go in school?	Categorical (0-9); never went to school (0) to > 4-year college (9)	N/A	level-1 and level-2
History of grade retention (Y)	Academics and Education Questionnaire	1	2	Have you ever repeated a grade or been held back a grade? Which grades?	yes/no; continuous	N/A	level-2
Low Verbal IQ (I) Guo et al., 2008 Rice & Brown, 1967	Add Health Picture Vocabulary Test (PVT)	1	1	N/A	70 or less (1); otherwise (0)	N/A	level-2
English not spoken in home**	General Introductory Questionnaire	1	1	What language is usually spoken in your home?	English (1), any other language (0)	N/A	level-2
Race/ethnicity* (Y)	General Introductory Questionnaire	1	2	What is your race? You may give more than one answer.	White (non-Hispanic) (0), Hispanic or Latino (1), Black or African American (2), American Indian or Native American (3), Asian or Pacific Islander (4), or Other (5)	N/A	level-1 and level-2

Note. *=Demographic control variable, **=Control for verbal IQ, Y=Youth self-report, I=Interviewer response, P=Parent self-report

Table 3

IRT W1 Violence Measure Results: Factor Loadings for Model 1 and Model 3

Item	Label	Model 1 λ	s.e.	Model 3 λ	s.e.
a	use or threaten to use a weapon to get something from someone	0.76	0.04	0.81	0.04
b	take part in a group fight	0.80	0.03	0.82	0.05
c	get into a serious physical fight	0.81	0.02	--------	-----
d	get into a fight where you were injured and had to be treated by a doctor or nurse	0.20	0.07	--------	-----
e	hurt someone badly enough to need bandages or care from a doctor or nurse	0.85	0.02	--------	-----
f	pull a knife/gun on someone	0.78	0.04	0.85	0.07
g	shoot/stab someone	0.85	0.03	0.90	0.06
h	Mean(c,e)	--------	-----	0.77	0.04

Table 4

Item Response Theory Item Parameter Estimates for the 5-Item W2 Violence Measure

Item	Label	Item parameter estimates			
		α	β_1	β_2	β_3
g	shoot/stab someone	3.6	2.12	2.62	
f	pull a knife/gun on someone	2.92	1.7	2.43	
h	Mean(c,e)	2.66	1.33	2.37	3.15
b	take part in a group fight	2.4	0.87	1.83	2.45
a	use or threaten to use a weapon to get something from someone	2.28	2.04	2.77	3.11

Table 5

Descriptive Statistics*

Variable Name	Wave 1		Wave 2		Grand Mean
	Mean	SD	Mean	SD	
Age	16	1.7	17	1.6	16.5
Probability of Violence	1.36	1.84	1.14	1.78	1.267
White	0.58	0.5	0.58	0.5	0.58
Black	0.23	0.42	0.23	0.42	0.23
Hispanic	0.1	0.58	0.1	0.58	0.1
Asian	0.03	0.18	0.03	0.18	0.03
Native American	0.01	0.08	0.01	0.08	0.01
Other	0.05	0.23	0.05	0.23	0.05
English Not Spoken at Home	0.066	0.25	0.066	0.25	0.066
Parent's Highest Education	3.37	2.23	3.37	2.23	3.37
Family Poverty	0.38	0.8	0.38	0.8	0.38
GPA	2.68	0.77	2.69	0.76	2.685
Peer Delinquency	2.58	2.64	2.85	2.73	2.715
A Daily Family Meal	0.53	0.5	0.52	0.5	0.525
Truancy	2.17	7.47	1.53	4.43	1.85
School Attachment	19.7	4.62	20	4.5	19.85
Depressive Symptoms	0.56	0.43	0.54	0.42	0.55
Drug Use	5.21	13.37	7.15	14.65	6.18
Alcohol Use	1.51	1.62	1.78	1.67	1.645
Low Verbal IQ	0.29	0.66	0.29	0.66	0.29
Repeated Grade	0.26	0.44	0.26	0.44	0.26

Note. *Results prior to centering continuous independent variables

Table 6

Results of Paired-Sample T-Tests

Variable	**Mean difference**	**t-value**
Violence	-0.26	-6.5***
GPA	-0.004	-0.25
School attachment	-0.14	1.52
Truancy	0.21	1.56
Peer delinquency	0.42	8.16***
A daily family meal	0.04	3.17**
Drug use	1.64	0.80
Depressive symptoms	-0.013	-1.6
Alcohol use	0.45	7.16***

Note. *p<0.05. **p<0.01. ***p<0.001. a=R-square for final model

Table 7

Correlation Matrix of All Variables

	Violence	Age	Race	Family Poverty	Parent Education	GPA	Peer Delinquency	A daily family meal	Truancy	School Attachment	Depressive Symptoms	Drug Use	Alcohol Use	English Not Spoken At Home	Low VIQ	Repeated Grade
Violence	1	0.01	0.08**	0.1**	0.11**	-0.2**	0.31**	0.09**	0.17**	-0.24**	0.16**	0.1**	0.24**	0.004	0.06**	0.12**
Age	0.01	1	-0.01	-0.02	0.09**	-0.05**	0.3**	0.25**	0.17**	0.01	0.14**	-0.03	0.17**	0.07**	0.05**	0.24**
Race	0.08**	-.01	1	0.09**	0.15**	-0.06**	-0.04**	0.05**	0.04**	-0.02	0.08**	0.02	-0.03	0.35**	0.21**	0.06**
Family Poverty	0.1***	-0.02	0.09**	1	0.18**	-0.15**	0.04**	0.004	0.04**	-0.05**	0.08**	0.03	0.03	0.01	0.19**	0.13**
Parent Education	0.11**	0.09**	0.15**	0.183**	1	-0.20**	0.08**	0.09**	0.12**	-0.10**	0.09**	0.03	0.05**	0.15**	0.18**	0.2**
GPA	-0.21**	-0.05**	-0.06**	-0.15**	-0.20**	1	-0.23**	-0.09**	-0.2**	0.27**	-0.18**	-0.06*	-0.13**	-0.01	-0.13**	-0.25**
Peer Delinquency	0.31**	0.3**	-0.04**	0.037**	0.08**	-0.23**	1	0.19**	0.21**	-0.22**	0.18**	0.2**	0.46**	-0.07**	-0.07**	0.12**
A Daily Family Meal	0.09**	0.25**	0.05**	0.004	0.09**	-0.09**	0.19**	1	0.11**	-0.11**	0.13**	-0.01	0.11**	-0.01	0.03	0.03*
Truancy	0.17**	0.17**	0.04**	0.041**	0.12**	-0.2**	0.21**	0.11**	1	-0.2**	0.13**	0.042	0.16**	0.01	0.02	0.11**
School Attachment	-0.24**	0.01	-0.02	-0.05**	-0.10**	0.27**	-0.22**	-0.11**	-0.2**	1	-0.36**	-0.07*	-0.13**	0.03*	0.004	-0.08**
Depressive Symptoms	0.16**	0.14**	0.08**	0.08**	0.09**	-0.18**	0.18**	0.13**	0.13**	-0.36**	1	0.03	0.13**	0.06**	0.14**	0.10**
Drug Use	0.10**	-0.033	0.02	0.03	0.03	-0.06*	0.2**	-0.01	0.04	-0.07*	0.03	1	0.24**	-0.02	-0.004	0.009
Alcohol Use	0.24**	0.166**	-0.03	0.03	0.05**	-0.13**	0.46**	0.12**	0.16**	-0.13**	0.13**	0.24**	1	-0.08**	0.02	0.08**
English Not Spoken At Home	0.004	0.07**	0.35**	0.011	0.15**	-0.01	-0.07**	-0.01	0.01	0.03*	0.06**	-0.02	-0.08**	1	0.3**	0.04**
Low Verbal IQ	0.06**	0.049**	0.21**	0.19**	0.18**	-0.13**	-0.07**	0.03	0.02	0.004	0.14**	-0.004	0.02	0.3**	1	0.12**
Repeated Grade	0.12**	0.24**	0.06**	0.13**	0.20**	-0.25**	0.12**	0.03*	0.1**	-0.08**	0.1**	0.01	0.08**	0.04**	0.12**	1

Note. *p<0.05, **p<0.01, ***p<0.001

Table 8

Results of Mixed Effects Modeling

	Fixed	Null	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fixed Effects						Parameter Estimates (s.e.)							
Intercept	1.74 ***	1.73 ***	1.35 ***	1.42 ***	1.32 ***	1.76 ***	1.58***	0.87***	0.85***	0.86 ***	0.81***	0.81***	1.23***
	(0.08)	(0.07)	(0.08)	(0.09)	(0.09)	(0.20)	(0.13)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.15)
Time	-0.31***	-0.31***	-0.32***	-0.30***	-0.32***	-0.32**	-0.36***	-0.37***	-0.38***	-0.38***	-0.34***	-0.34***	-0.46***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
Age			0.03	-0.02	-0.01	-0.17***	-0.09**	-0.07***	-0.10***	-0.09**	-0.09***	-0.09***	-0.21***
			(0.02)	(0.02)	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Race			0.10**	0.09**	0.08**	0.13	0.14**	0.12***	0.10***	0.11***	0.11***	0.11***	0.16***
			(0.03)	(0.03)	(0.03)	(0.6)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Family Poverty			0.15***	0.12**	0.15***	0.22***	0.26***	0.15***	0.15***	0.15**	0.14***	0.13**	0.24***
			(0.04)	(0.04)	(0.04)	(0.09)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Highest Parent Education			0.08***	0.04*	0.07***	0.15***	0.13***	0.07***	0.05***	0.05***	0.05**	0.05**	0.10***
			(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.08)	(0.01)	(0.01)	(0.01)	(0.02)
GPA				-0.21***									
				(0.04)									
School Attachment				-0.07***									
				(0.03)									
Truancy				0.03***									
				(0.004)									
English Not Spoken at Home				-0.24									
				(0.15)									
Low Verbal IQ				0.08									
				(0.06)									
History of Grade Retention				0.19***	0.36***				0.32***	0.32***	0.32***	0.32***	0.53***
				(0.02)	(0.08)				(0.08)	(0.08)	(0.07)	(0.07)	(0.11)
Depressive Symptoms						0.37**	0.60***						
						(0.14)	(0.10)						
Drug Use						0.01***							
						(0.002)							
Alcohol Use						0.25***							0.22***
						(0.04)							(0.03)
Peer Delinquency								0.18***	0.18***	0.18***	0.18***	0.18***	0.12***
								(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
A Daily Family Meal								0.15**	0.15**	0.15**	0.17**	0.17**	0.11
								(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)
Age*Peer Delinquency										-0.006			
										(0.006)			
R-square[b]			0.21	0.18	0.24	0	0.09	0.49	0.51	0.50	0.58	0.29	0.29

Table 8
(continued)

Random Effects	Covariance Parameters (s.e.)												
Intercept		1.50*** (0.07)	1.36*** (0.09)	1.16*** (0.07)	1.16 *** (0.07)	1.89 *** (0.20)	1.49 *** (0.12)	1.07*** (0.07)	1.02 *** (0.06)	1.02** (0.06)	0.75*** (0.06)	0.92*** (0.07)	1.08*** (0.11)
Peer Delinquency											0.03*** (0.003)		
A Daily Family Meal												0.43*** (0.09)	
Alcohol Use													0.11*** (0.03)
R-square[c]											0.05	0.03	0
-2 Restricted Log-Likelihood[a]	56804	18550	18479	16392	16586	4052	8463	17657	16331	16592	17543	17618	8072

Note. *p<0.05. **p<0.01. ***p<0.001. a=Estimate includes both level 1 and 2. b=between-individual variance explained. c=within-individual variance explained.