Predicting Juvenile Recidivism Using Latent Growth Modeling

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Abstract

Although this study found evidence that the “age-crime” curve is not just a group phenomenon, but an individual phenomenon, there was also evidence that this is not the ideal way to model delinquency for all youth. Mixture modeling, using two groups, showed that many youth who offend are “one timers” who offend once at any time during their adolescence (and every age is equally likely, contrary to Moffit’s “adolescent limited” typology). The second group represents youth who offend more frequently (about once a year at their peak) and increase up through age 16, then decrease. Latent growth modeling, as used in this case, does not improve prediction of delinquency through adolescence over more commonly used methods. Post-hoc analyses suggest that recidivism may best be modeled as a residualized change score, predicted from the two prior time points to the one being estimated.

Predicting Juvenile Recidivism

Using Latent Growth Modeling

Background

Developmental Anti-Social Behavior

It is well established in the developmental psychology literature that antisocial behavior (ASB) follows a non-linear trajectory in adolescents and that early initiation of ASB is associated with increased severity and persistence of this behavior later in life (Moffit, 1993). Unfortunately, this understanding has not translated to an improvement in the way that juvenile risk assessments make use of offense history to predict the likelihood of future delinquent involvement. The common practice of creating a simple additive score to predict future recidivism essentially discards of potentially useful data: the age at each offense.

Latent Growth Curve modeling (LGM) is a common technique that developmental psychologists have used to look at juvenile delinquency over time. Most of these studies, however, have made use of self and parent report questionnaires (Stoolmiller, 1994; Mason, 2001; Wiesner and Windle, 2004). Common shortcomings of many of these developmental trajectory models of delinquency is they make use of smaller time frames within the youths' development . For example, Wiesner and Windle (2004) only looked at ages from 15.5 to 17. No studies were identified that attempted to make use of LGM for the purpose of predicting recidivism.

Theoretical

This study posits that overt anti-social behavior is a latent trait underlying the observed variable of delinquency, (operationalized as law breaking events). Moreover, it is assumed that this trait is measured with a great deal of error. This underlying trait differs a great deal from individual to individual, but has a similar shape across individuals. Presumably it accelerates in early adolescence and then slows in late adolescence. It reaches a peak and then decreases in early, into late adulthood. Essentially, it follows a bell curve that replicates Moffit's (1993) curve of offenses by age (see figure 1). Those who are "early starters" would also be "late finishers", consistent with Moffit's theory of life course persistent vs. adolescent limited youth. Moffit argues that prevalence rates for arrests by age that show a peak of activity around age 17 can be explained by new, adolescent limited offenders joining the ranks of life course persistent offenders. She supports this claim using national statistics of new offenders by age that shows a constant increase up to age 16 and then a sharp decrease. This finding, though true, does not exclude the additional influence of increases in the number of offenses by age as well.

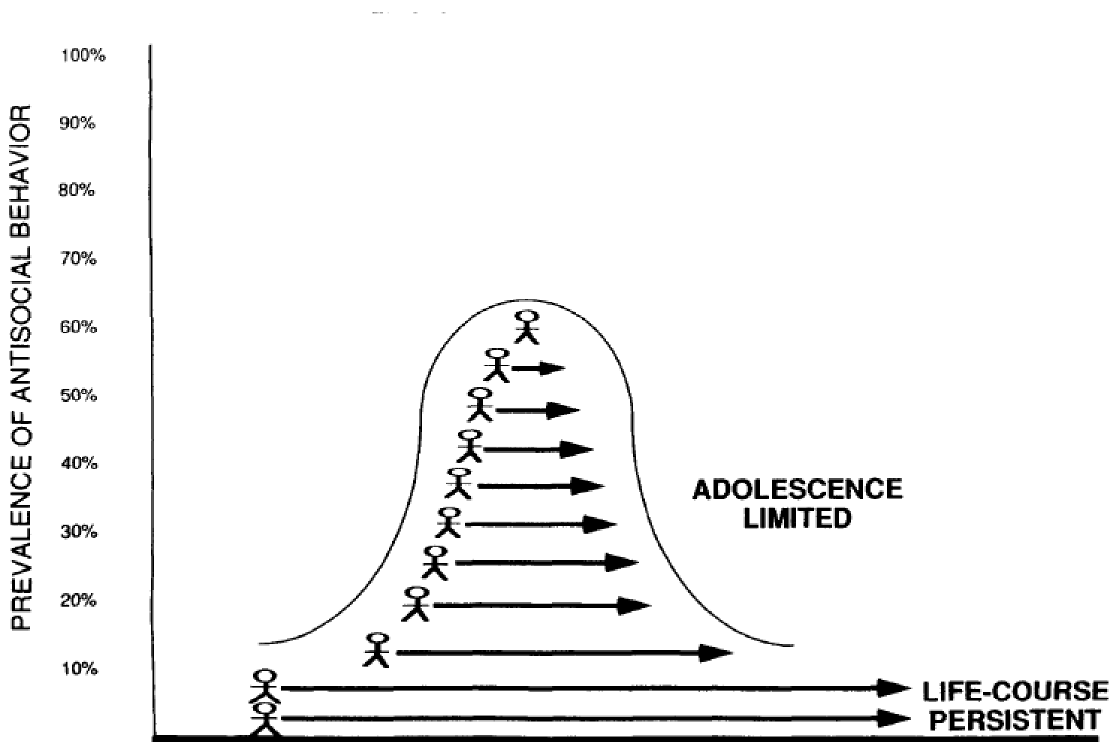
Stolzenberg and D'Alessio (2008) break down the relationship between age and offense rate by gender, ethnicity, type of crime, and solo vs. communal offending. They conclude the "age crime curve", or the parabolic curve that Moffit wrote about, is virtually unchanged within these subgroups. In other words, the finding that delinquency increases through the teenage years and then decreases through early adulthood is true for all ethnic subgroups and types of offenders examined in their research. This study, unfortunately, cannot distinguish between increases in number of offenders or increases in number of offenses per individual. Farrington (2005) writes that it is still contentious whether individual frequency of offending peaks at late adolescence, or whether there is no relationship between age and frequency of offending. In investigating this phenomenon of rate of offending, many researchers (see Loeber and Snyder, 1993) make a theoretical assumption that youth should be characterized as active and non-active, and that offense rates should only be looked at during the youth's active period.

This study hypothesizes that frequency of offending *does* peak in middle adolescence, and that offenses early in life will confer risk of a higher frequency of offenses in late adolescence. But, in contrast to many researchers, a single discrete 'age at first arrest' is not the most predictive measure. Instead, recorded offending behavior is an observed measurement (with a great deal of measurement error) of a latent trait, overt anti-social behavior, much of which is either not illegal or not observed by authorities. This latent trait, as understood in this context, has a non-linear trajectory that peaks in late adolescence, and for most youth, desists later in adulthood. Importantly, this theory predicts that the *shape* of this curve is similar across individuals, but the height of the curve varies between individuals.

This theory would have several implications for prediction:

1. An offense earlier in life (between age 8 and 12) would confer greater risk for offenses later in adolescence than an offense in mid-adolescence (13-15).
2. Predicting recidivism based on one year prior offenses, without assuming non-linear growth, would result in a biased estimate for all youth: an underestimate for younger youth and an overestimate for older youth.
3. Number of offenses at *every* age hold important information for approximating the latent curve of delinquency. Using every age should reduce error in approximating delinquency. Using just one (age at first arrest) would confer too much error to any model.

Figure 1: Moffit's Theoretical Diagram to Explain Changes in Prevalence Rates of Arrests by Age



Methods

Latent Growth Curve Modeling

Latent growth curve modeling (LGM) provides a framework for estimating non-linear trajectories in repeated measure designs. Instead of analyzing mean differences, LGM can identify *individual* differences on some latent trait that changes over time (Duncan and Duncan 2004). Moreover, because it is a special case of structural equation modeling, it allows for testing of a growth model versus a competing non-growth model as well as absolute tests of model fit.

McArdle and Nesselroade (2003) lay out the basic form of the latent growth curve model:

$$Y[t]_n = \gamma_{0,n} + A[t]\gamma_{s,n} + e[t]_n$$

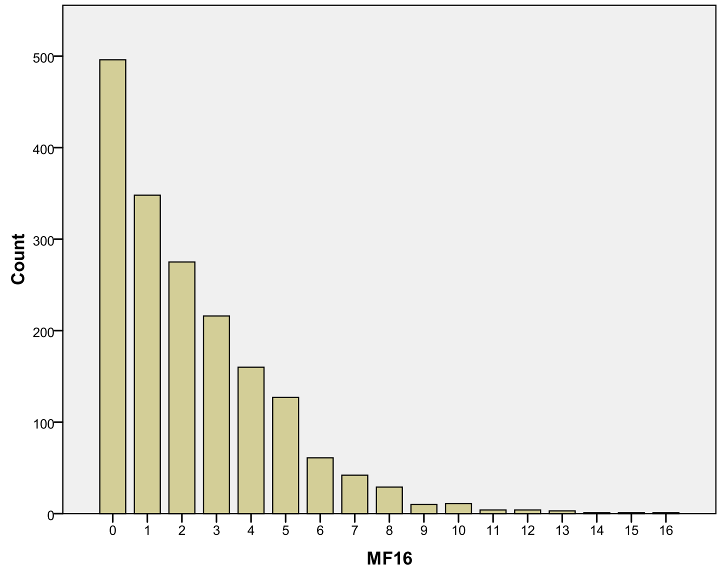
$\gamma_{0,n}$ represents the intercept for person n and A[t], the effect of the slope (γ_s) for person n ($\gamma_{s,n}$) on the observation at each time t ($Y[t]_n$). In this study two of the A[t] paths will be fixed to scale the rate of change, while the rest will be estimated to allow for non-linear growth. The null model, or no growth model is:

$$Y[t]_n = \gamma_{0,n} + e[t]_n$$

The null model posits that scores at each time t are simply the function of the mean for person n ($\gamma_{0,n}$) and error. This null model is equivalent to a mean or sum score of the observations across times, or that each subsequent score can best be estimated by taking the mean of the previous scores.

In its most general form, latent growth modeling assumes that there is a latent growth function (a line, a curve or a parabola) that underlies observations for each individual. Each observation in time(Y[t]) for each person is assumed to have measurement error, but to be a manifestation of that unobserved curve or line. For a linear latent model, this latent line can be described by two parameters for each person: the slope and the intercept. A multilevel model can now use this collection of slopes and intercepts as two criterions that have the error of each individual observation removed.

Figure 2: Histogram of number of offenses for a sample of court involved 16 year olds



The central problem encountered when analyzing juvenile offense data is the decidedly non-normal distribution of the number of offenses in a given time period. Figure 2 shows a typical shape for this data, with a modal value of 0 offenses/ time period. This would represent a clear violation of the assumption of multivariate normality for Maximum Likelihood estimation of the SEM growth curve model. This data rarely exhibits even univariate normality.

It is proposed that Bayesian estimation of the growth curve model will allow this model to be estimated accurately, because it makes no assumptions about the posterior distribution (Scheines, Hiojtink and Boomsma, 1999).

The dependent variables will be the number of offense events per year by youth. (In the models they will be written as: MF16 to represent total number of misdemeanor or felonies at age 16). Offense events are operationalized as unique misdemeanor, felony, status or technical offense, with a maximum of one offense per calendar day.

Figure 3 depicts the hypothesized growth model and Figure 3, the corresponding null model. Note, the error variances are not posited to be equal, as in some LGM's (i.e. the model is not expected to predict the same amount of variance across ages). All of the intercepts will be fixed to zero and the means and variances of the slope and intercept will be estimated. The priors for the Bayesian estimation will all be non-informative (uniform distribution).

Absolute goodness of fit will be calculated based on the posterior predictive p, and the relative goodness of fit for competing models will be compared using the Deviance Information Criteria (DIC). The DIC can be used for both nested and non-nested model comparison. Smaller values of the DIC represent better fit than larger values, and models within 5 points on the DIC are considered not different from one another (Lee, 2007). Bayesian estimation uses “credible intervals” in place of confidence intervals. Whereas confidence intervals are based on assumptions about sampling distributions, credible intervals are based on the obtained distributions of the parameter of interests from repeated simulations of the model. For most models, 95% credible intervals will be presented. These represent the bounds of the inner 95% of the parameter estimates.

Figure 3: Hypothesized growth model

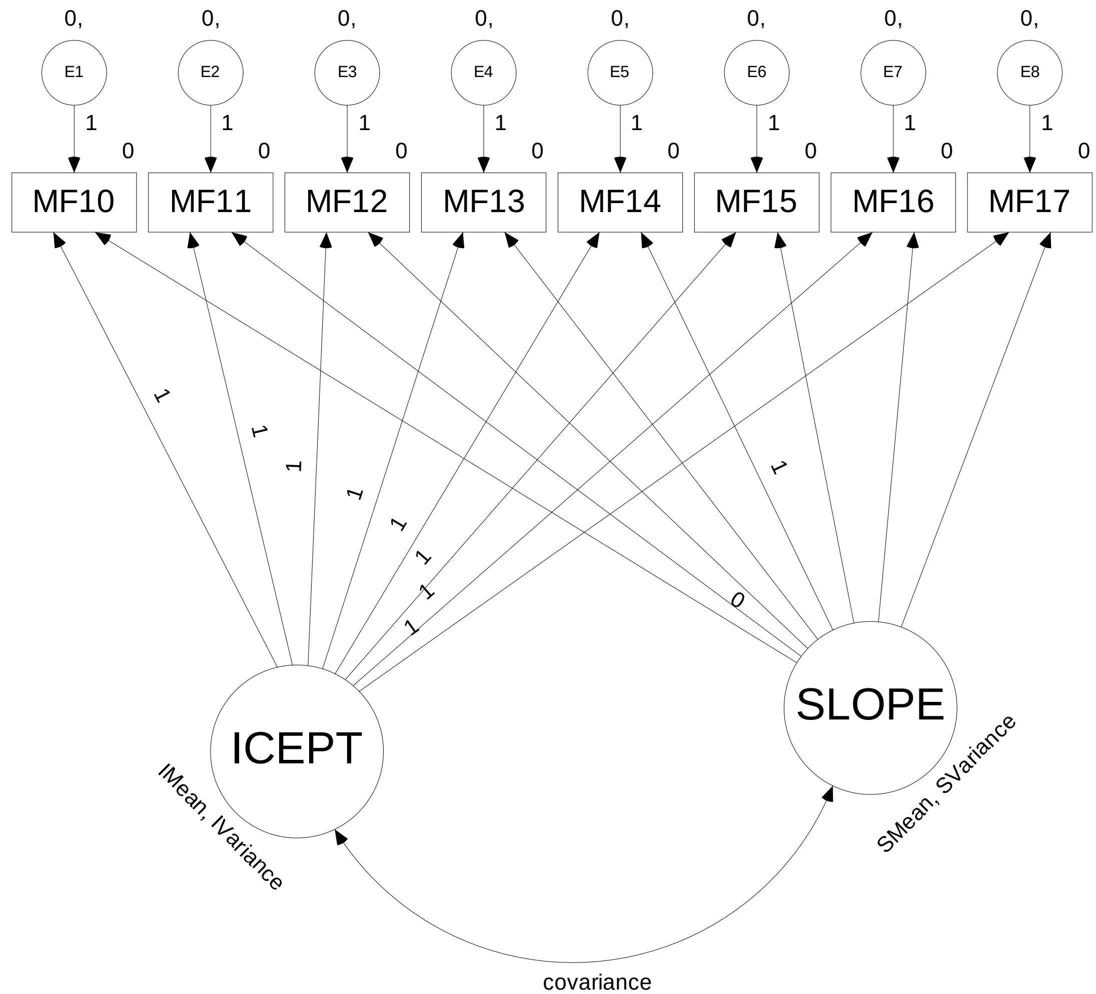
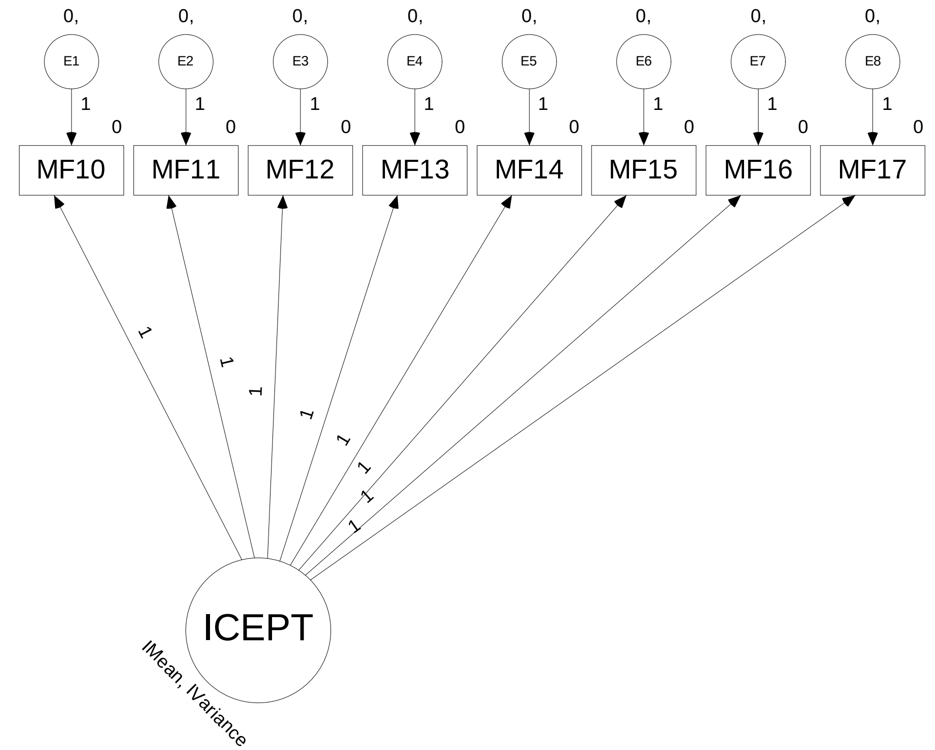


Figure 4: No-growth null model.



In addition to testing whether juvenile offenses are best modeled using a non-linear latent growth model, the relationship of gender to offending will be tested. The hypothesis is that the shape of growth will not differ between genders, but rather there will be mean differences in slopes and intercepts between males and females. In other words, males and females will not differ on the essential shape of the curve of offending, but rather on their intercepts and slopes of this curve. To test this hypothesis, a multiple group analysis will be employed based on a procedure similar to testing for measurement invariance across groups (McArdle & Nesselroade, 2003). Two competing stacked models will be tested, one where the estimated paths of the slope on each age are fixed between genders and one where they are free to vary. In other words, these models are testing whether

$A[t]^{(m)} = A[t]^{(f)}$ (for all estimated A[t])

If these two models do not differ significantly based on the Deviance Information Criteria, then it is then appropriate to test whether the variance components of the slope and intercept are equivalent, with the A[t] paths equated between groups. Again, two competing models, one with intercept and slope variances equated and one where they are freely estimated between groups will be compared. Finally, if these two models are not significantly different, then a final model can employed testing for mean differences on the slope and intercept between groups. Following McArdle and Nesselroade (2003), this can be tested without using a stacked model, but by a simple mixed effects model (see figure 4). The unstandardized paths from “Sex” to the slope and intercept represent the mean differences between males and females on each latent trait (with the intercept representing the mean of whichever group is coded ‘0’).

This stacked model procedure has the advantage of testing both aspects of the hypothesis: whether there exist structural differences between groups and whether there are mean differences between groups.

Participants

All individuals with dates of birth between 1/1/1990 to 12/31/1991 and any felony, misdemeanor, status or technical charge in the state court database were selected. This range was selected to collect individuals who had already turned 18, and would have complete offense data for each age period. These criteria identified 25,883 individuals. 1,011 individuals (3.9%) who had out of state addresses listed were removed. Table 1 shows this sample broken down by gender and race/ethnicity.

Table : 1
Sample Demographics

Group		N	%
Gender			
	Male	15,954	64.1
	Female	8916	35.8
Race/Ethnicity			
	White	15,736	63.3
	Latino/Hispanic	4,660	18.7
	African American	555	10.0
	Native American	470	1.9
	Asian	341	1.4
	Not Specified	2,529	10.1

The sample was divided into a primary sample (N=12,546) and a holdout sample (N=12,326) using the random number generator in SPSS 18 . All model testing was performed on the primary sample. The holdout sample was used for testing the r^2 of the model estimated from the prior step. For the final unconstrained growth model, a cross validation was performed (both groups were estimated and then the parameter estimates were used to create an r^2 value for the opposite model).

Missing Data

Because the selection criteria identified only individuals who had turned 18 and had only lived in Utah, there was no missing data for number of offenses at each age. 36 individuals (.1%) were missing Race/Ethnicity data and 2 individuals (less than .1%) were missing gender data. For any analyses that included these variables, Bayesian imputation was performed concurrently with the analysis (in AMOS 17).

Results

Intercept Only Model

The intercept only model posited that a juvenile's offending over time can be modeled by just their own average number of offenses per year. At level one:

$$Offenses_{it} = \beta_{0i} + e_{it}$$

As in all models run, the error variances were heterogeneous.

Table 2 shows the Bayesian estimation of the intercept only model. For this model, the mean intercept across individuals was .04 and was significantly different from zero based on the 95% Bayesian credible intervals. This predicts that the average offending across individuals is .04 offenses per year. The variance of the intercept (σ^2= .008), also significantly differed from zero indicating that the average offending varied significantly across individuals.

Table 2

Bayesian Unstandardized Estimates: Intercept Only Model Predicting Number of Offenses at Each Age

Parameter	Mean	95% Lower	95% Upper
Means			
Intercept	0.047*	0.044	0.049
Variances			
Intercept	0.008*	0.008	0.009

DIC=18,732 ; ppp=.00

*95% Credible Interval did not include zero

Linear Change Model

Time in this model was scaled so that a one unit change represented the increase from age nine to age 17 (to make the scale of the parameters more convenient). Table 3 presents the linear growth model Bayesian estimates.

Table 3
Bayesian Unstandardized Estimates: Linear Growth Model Predicting Number of Offenses at Each Age

Parameter	Mean	95% Lower	95% Upper
Means			
Intercept	-0.022*	-0.025	-0.019
Slope	0.524*	0.511	0.538
Variances			
Intercept	0.006*	0.005	0.007
Slope	0.223*	0.209	0.237
Covariance			
Slope and Intercept	-0.006*	-0.008	-0.004

DIC=7,335 ; ppp=.00
*95% Credible Interval did not include zero

In this model, the intercept, or predicted number of offenses at age 9 was negative (B = -.02) and was significantly different from zero. The variance on the intercept was also significantly different from zero (σ^2=.006) indicating that individual significantly differed on their predicted number of offenses at age 9, and one standard deviation in either direction included positive values, but overall, predicted offending at age 9 was close to zero. The average slope, or predicted increase in number of offenses per year from age 9 to age 17 was .524, or close to one offense every two years. This average predicted value was significantly different from zero. The variance on the slope was also significantly different from zero (σ^2=.223) and was larger than the variance on the intercept. This indicates that individuals varied more on their change over time than they did on their predicted levels of offending at age 9. This model predicts that the middle two standard deviations of individual slopes in this sample would range from .06 to 1.006, or increases close to zero and others close to one offense per year. The covariance between the slope and the intercept was -.006 and was significantly different from zero, indicating that higher predicted offending at age 9 actually predicted more modest increases in offending over the course of adolescence.

The absolute model fit of the linear model was not adequate, but the relative model fit improved over the no growth model (The DIC decreased from 18,732 to 7,335). The negative predicted values of offending at age 9 also suggest that a linear model is not an acceptable one for this data.

Table 4
Bayesian Estimation: Unconstrained Growth Model Predicting Number of Offenses at Each Age

Parameter		Mean	95% Lower	95% Upper
Means				
	Intercept	0.011*	0.007	0.014
	Slope	0.651*	0.628	0.673
Variances				
	Intercept	0.008*	0.007	0.008
	Slope	0.307*	0.287	0.328
Covariance				
Slope and Intercept		0.002*	0.0003	0.0044
Slope Weights				
	Age 9	0†		
	10	0.023*	0.017	0.028
	11	0.053*	0.046	0.06
	12	0.156*	0.143	0.168
	13	0.337*	0.319	0.356
	14	0.571*	0.545	0.597
	15	0.916*	0.881	0.954
	16	1.114*	1.07	1.15
	17	1†		

DIC = 3,102 ; ppp=.00

†Parameters fixed to scale model

Table 4 presents the Bayesian estimates of the unconstrained model. In the unconstrained model, the slope was scaled the same way the linear slope was (age 9 was coded as time 0 and age 17 was time 1) but all other times besides the two used to scale the model were allowed to be estimated from the data, allowing for non-linear change. The estimated slope weights indicated that offending, on average, increased slowly from age 9 to 12 and then rapidly increased from age 13 to 16 and then decreased from age 16 to 17. This was confirmed by the slope weight at age 16 being significantly greater than 1 (95% CI = 1.07, 1.15).

In this model, the predicted offending at age 9 was positive and significantly different from zero (B = .011). The intercept variance was also significantly different from zero, suggesting that individuals varied on predicted offending at age 9. The average slope, or predicted increase in offending from age 9 to age 17, was .651 and was significantly different from zero. Because the weight at age 16 went above 1, this would predict individuals, on average, increase to .725 offenses per year above the intercept before decreasing to .651. The variance on the slope (σ^2=.307) was also significantly different from zero, indicating that individuals varied on change in offending over time. Figure 3 presents plots of the unconstrained model at the mean slope and intercept, with additional plots one standard deviation above and one standard deviation below the mean slope.

This model was also not adequate by the measure of absolute fit (ppp=.00) but was an improvement from the linear model (Reduction in DIC = 4,233).

Table 5

Maximum Likelihood Bootstrap:
Unconstrained Growth Model Predicting
Number of Offenses at Each Age

Parameter		Mean	95% Lower	95% Upper
Age				
	9*	0†		
	10	0.023*	0.011	0.033
	11	0.053*	0.039	0.068
	12	0.156*	0.127	0.183
	13	0.336*	0.299	0.378
	14	0.570*	0.524	0.620
	15	0.915*	0.860	0.987
	16	1.114*	1.054	1.162
	17*	1†		

Note: number of bootstrap samples=200
†Parameters fixed for scaling purposes
*95% Credible Interval did not include zero

A maximum likelihood bootstrap was performed to determine the degree to which sampling would influence the estimation of the time weight parameters. 200 bootstrap samples were drawn (bootstrap samples are random sampling with replacement from the original data to reproduce the original sample size). The mean for each parameter is the mean maximum likelihood estimate from the 200 samples. The 95% confidence intervals are the bounds of the inner 95% of the maximum likelihood estimates for that parameter. Table 5 presents the results of the 200 bootstrap estimates. For this analysis, the mean estimates were identical to the Bayesian estimates to the third decimal place (with differences of .001 due to rounding). The 95% confidence intervals indicate that the estimates of the weights could vary for estimating earlier ages, but stabilized when estimating later ages. More than 95% of the bootstrap samples contained estimates of the weight for age 16 that were above the estimate for age 17, indicating that this non-linear trend is relatively stable.

Figure 3: Predicted Number of Offenses by Age (Unconstrained Model)

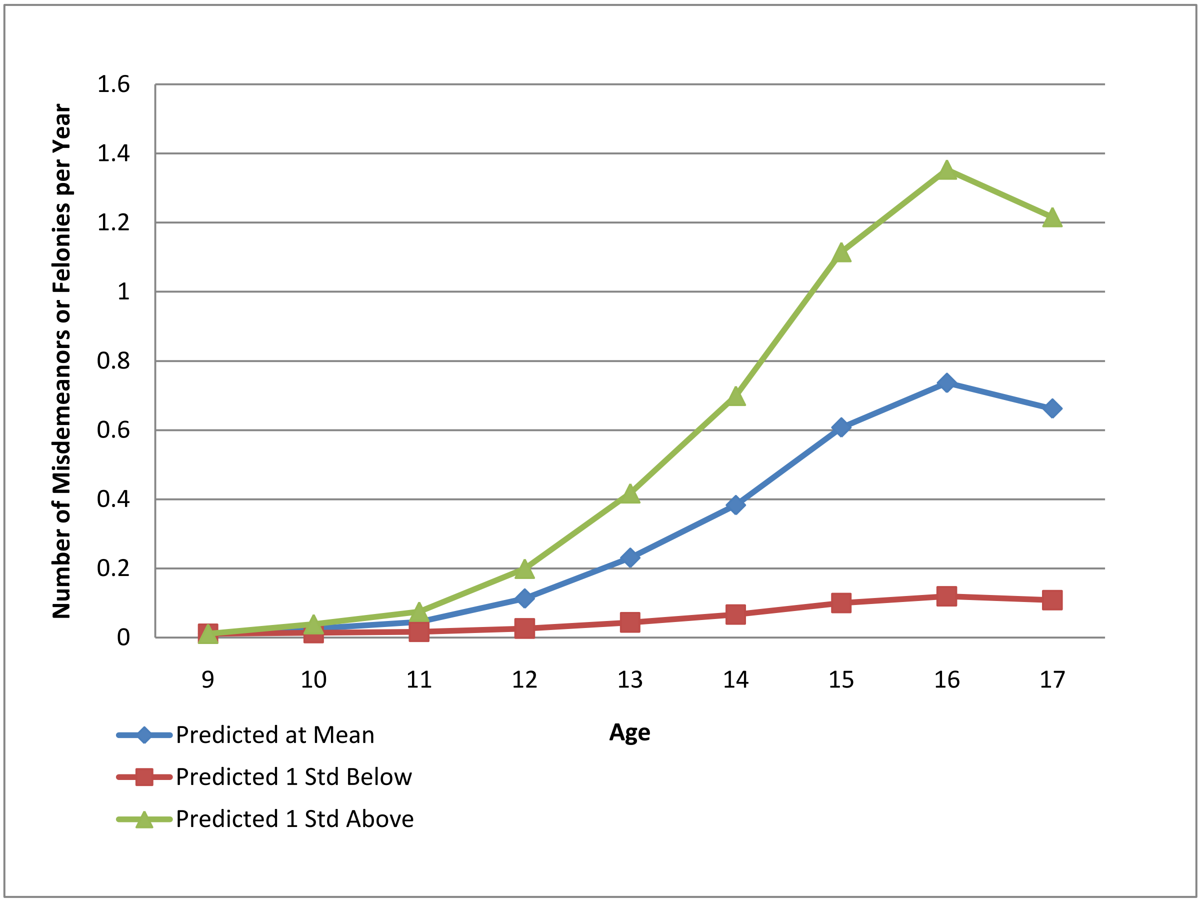


Table 6

Bayesian Estimation: Quadratic Growth Model Predicting Number of Offenses at Each Age

Parameter	Mean	95% Lower	95% Upper
Means			
Intercept	0.006*	0.003	0.009
Slope	0.001	-0.002	0.004
Quad	0.017*	0.017	0.018
Variances			
Intercept	0.007*	0.007	0.008
Slope	0.011*	0.01	0.011
Quad	0.001*	0.001	0.001
Covariances			
Slope and Intercept	-0.002*	-0.003	-0.001
Slope and Quad	-0.002*	-0.002	-0.002
Intercept and Quad	0.0002*	0.0001	0.0004

Note: Time coded 0 at age 9, 8 at age 17
ppp: .00; DIC: 3,033

For the quadratic model, time was coded 0 at age 9 and 8 at age 17. In this model the mean intercept and quadratic coefficients differed from zero, but not the slope (B=.001, 95% CI: -.002, .004). This would indicate that a large portion of the linear main effect from the previous models can be described with a quadratic term. The intercept, slope and quadratic terms all had significant variances, indicating that individuals varied on all three of these coefficients.

This model showed some improvement over the unconstrained model.

Table 7

Bayesian Estimation: Cubic Growth Model Predicting Number of Offenses at Each Age

Parameter	Mean	95% Lower	95% Upper
Means			
Intercept	0.008*	0.005	0.01
Slope	0.022*	0.018	0.026
Quad	-0.001	-0.004	0.001
Cubic	0.002*	0.001	0.002
Variances			
Intercept	0.008*	0.007	0.009
Slope	0.011*	0.009	0.013
Quad	-0.004	-0.0013	0.001
Cubic	0.00005*	0.00001	0.00008

Note: time was coded as 0 for age 9 and 8 for age 17
*95% Credible Interval did not include zero
ppp= .00 ;DIC = 2,758

The cubic model showed some improvement in model fit over the quadratic model and the unconstrained model: the DIC was reduced by 275 from the quadratic model. Table 7 shows the Bayesian estimates for the cubic growth model. In this model, the slope was significantly different from zero, but now the quadratic term was no longer significantly different from zero. Neither the cubic nor the quadratic terms had significant random effects. This model suggests that the main effects could be described with just an intercept, linear and cubic term, and that the cubic term was essentially a fixed factor.

Stacked Model Male-Female

Two competing stacked models were used to test for measurement invariance between male and female offenders. Both models were versions of the "unconstrained" model described above. In both models the error variances were constrained across the two groups and the means and variances for the slope and intercept terms were allowed to vary between males and females as was the covariance between the slope and the intercept. The main difference was in the "weights not equated" model the weights from the slope to each time point were allowed to vary between males and females and in the "weights equated" model they were fixed to be the same across the two groups. Whether there is improvement in the deviance information criteria is essentially the test of whether these weights really are different between males and females. Table 8 shows the Bayesian estimates for the two stacked models, one with the weights equated and one where they were allowed to vary.

The deviance information criteria for the "weights not equated" model was reduced by 151, indicating that the regression weights from the slope to each time point were significantly different across the groups. (And simply adding gender as a second level predictor would violate the assumption of measurement invariance). As was expected, the female group had a lower mean slope, indicating that females generally offend at a lower rate than males (in both the equated and non equated models, the 95% credible intervals for the two slopes did not overlap). Though females had lower average offending rates, their trajectory peaked more sharply than their male counterparts (a maximum slope weight of 1.2 instead of 1.05). The prediction plot for the stacked model by gender with weights not equated can be seen in figure 4.

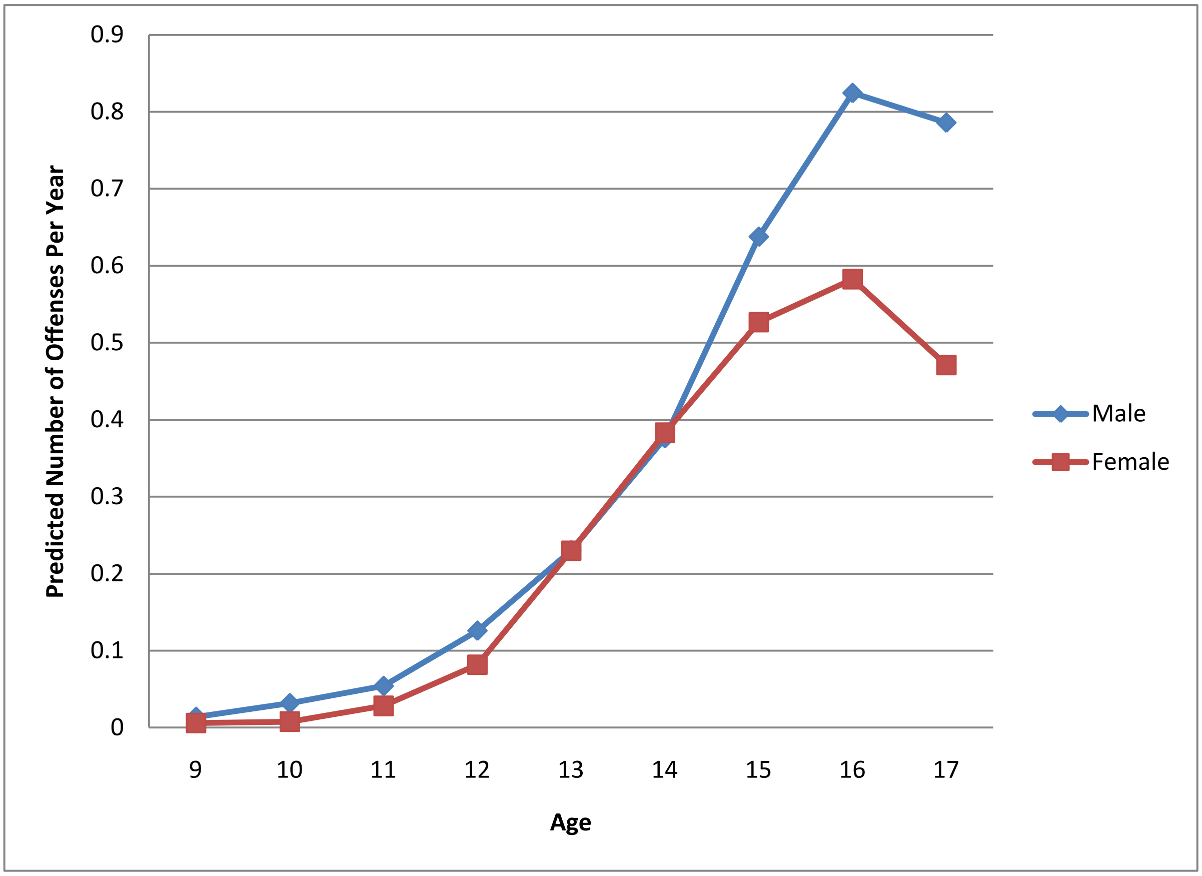
Table 8

Bayesian Estimation: Unconstrained Growth Model Predicting Number of Offenses at Each Age (Stacked by Gender)

	Weights Not Equated		Weights Equated	
Parameter	Male	Female	Male	Female
Means				
Intercept	0.014*	0.006*	0.015	0.002*
Slope	0.772*	0.465*	0.733*	0.580*
Variances				
Intercept	0.013*	-0.001*	0.013*	-0.001*
Slope	0.488*	0.083*	0.733*	0.092*
Covariance				
Slope and Intercept	-0.003	0.007*	-0.002	0.008*
Slope Weights				
Age 9	0.000†	0.000†	0.000†	
10	0.023*	0.004	0.019*	
11	0.052*	0.048*	0.052*	
12	0.145*	0.163*	0.149*	
13	0.280*	0.481*	0.315*	
14	0.469*	0.811*	0.527*	
15	0.808*	1.120*	0.863*	
16	1.050*	1.240*	1.087*	
17	1.000†	1.000†	1.000†	
Model Fit				
DIC	7439		7590	
PPP	0.00		0.00	

*95% Credible Intervals did not include zero
†Parameter Fixed

Figure 4: Predicted Number of Offenses By Age (Stacked Model by Gender)



Latent Growth Mixture Modeling

Latent Growth Mixture modeling (LGMM) was used to look at possible subpopulations in the data. LGMM looks for unobserved discrete groupings of individuals based on the growth model specified. In this model two unobserved groups were specified. The basic model was the same as the "unconstrained" model and the weights from the slope to the observations were allowed to vary between groups. The means for the slope and intercept were also allowed to vary between groups. In order to estimate this model, the variances were fixed for the slope and the intercept to 1. The errors were also forced to be homoscedastic over time and equal across groups. Table 9 presents the Bayesian estimates for the unconstrained LGMM with two groups.

The estimated model picked out a first group that could best be described as very low level offenders that stayed at a constant level of offending across time. Their predicted offending rate at age 9 was less than one offense per 10 years and it increased by about that much over the course of adolescence. This group (“group 1”) made up an estimated 66% of the total group.

The second group made up 33% of the total sample and could best be described as moderate level offenders who increased in offending and peaked at age 16 then returned to a lower rate at age 17. Their predicted offending at age 9 was about the same as the first group, but they increased to an average offending rate of 1.75 offenses per year. Their trajectories more closely resembled the original group, but with a higher slope coefficient. Figure 5 shows the prediction plot for the latent growth mixture model.

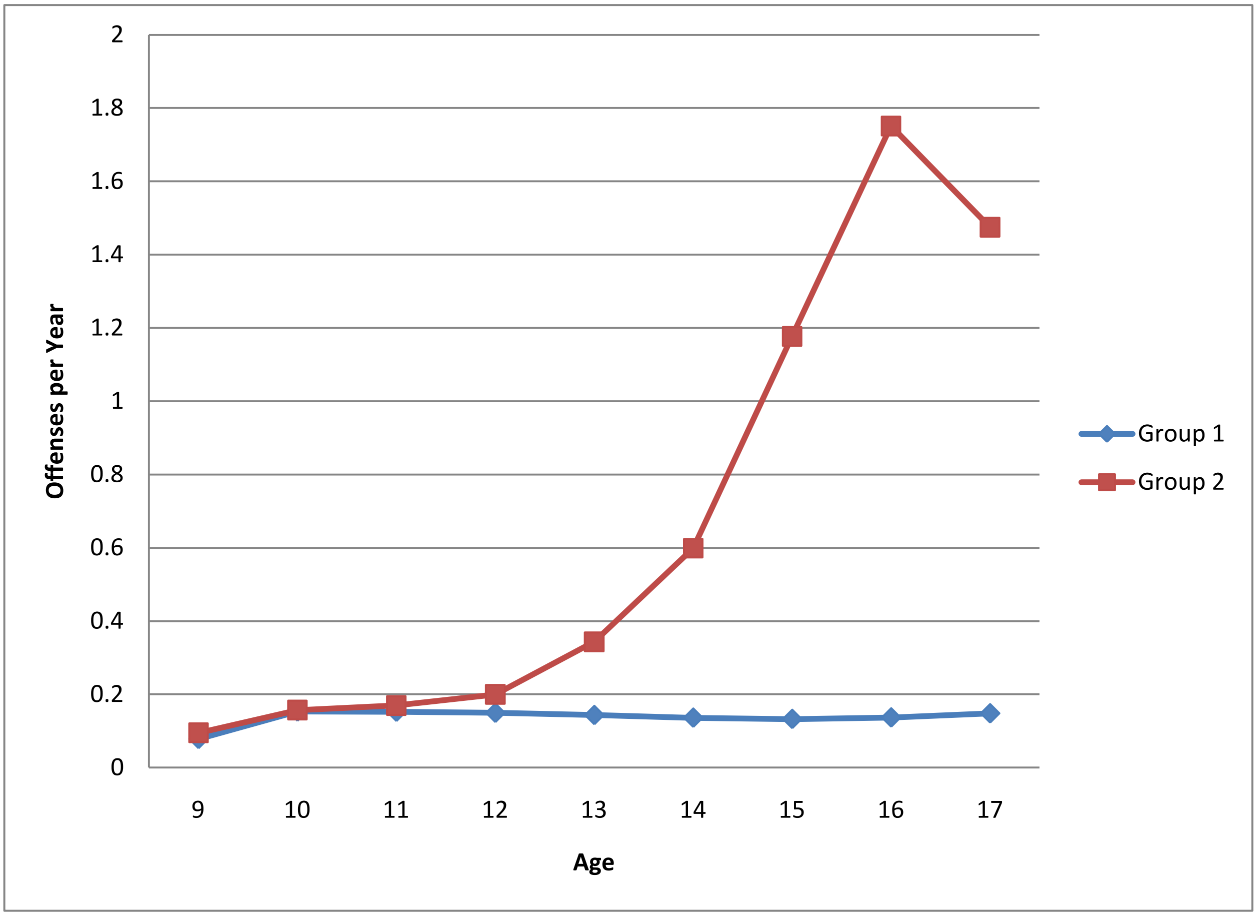
Table 9

Bayesian Estimation: Unconstrained Growth Mixture Model Predicting Number of Offenses at Each Age

	Group 1			Group 2		
Parameter	Mean	95% Lower	95% Upper	Mean	95% Lower	95% Upper
<u>Means</u>						
Intercept	0.078*	0.05	0.106	0.095*	0.059	0.132
Slope	0.07*	0.041	0.099	1.38*	1.4	1.43
<u>Variances</u>						
Intercept	1†			1†		
Slope	1†			1†		
<u>Covariance</u>						
Slope and Intercept	-1.031*	-1.032	-1.031	-0.551*	-0.58	-0.52
Slope Weights						
Age 9	0†			0†		
10	1.07*	1.043	1.097	0.045*	0.027	0.062
11	1.06*	1.04	1.094	0.054*	0.036	0.071
12	1.02*	1.001	1.054	0.076*	0.058	0.094
13	0.933*	0.904	0.962	0.18*	0.161	0.198
14	0.83*	0.799	0.861	0.365*	0.346	0.384
15	0.781*	0.749	0.814	0.784*	0.761	0.808
16	0.839*	0.81	0.867	1.2*	1.18	1.23
17	1†			1†		
Proportion	0.66	0.65	0.67	0.33	0.32	0.34

*95% Credible Intervals does not include 0

Figure 5: Two Group Latent Growth Mixture Model



Predicting Recidivism

All models above were estimated using a random half of the data (the "estimation sample"). All models in this section were tested on the other random half of the data (the "holdout sample"). To predict number of offenses at ages 13 through 17, each algorithm was allowed to make use of all prior ages, but could not make use of the actual mean or variance of the dependent variable from the holdout sample. The time weights for the "unconstrained model" were calculated from the estimation sample.

The "baseline model" was a guess of the average offenses per year at each age from the estimation sample. This is a very sample dependent way of predicting recidivism, and does not discriminate individuals, but does give some comparison for comparing mean absolute error values between models.

First, a "naïve" model was estimated. This is the model that would be used if a researcher did not separate offenses by age, but simply added the priors together, and controlled for age as a linear covariate. To estimate this model, a simple OLS linear regression was used at each age after 12. Prior offenses in this model were just the sum of all previous offending events.

$$Predicted\ Offenses = \beta_0 + \beta_1 PriorOffenses + \beta_2 CurrentAge$$

The unstandardized regression weights from the estimation sample were -.9235 for the intercept, .1379 for prior offenses and .0768 for current age.

For the "mean" model, each successive age point was modeled as the average of all previous time points:

$$Y[t]_i = \left(\frac{1}{n}\right)(\,Y[t-1]_i + Y[t-2]_i \ldots) + e_{it}$$

The "unconstrained" model estimated a slope and an intercept for each person (i), based on each prior time point [t], in order to predict the future time points. The slope had an optimal weighting (that was estimated in the previous section) at each time point $A[t]$.

$$Y[t]_i = Intercept_i + A[t]Slope_i + e_{it}$$

Note: the $A[t]'s$ are fixed in this model. The person parameters are all that are being estimated. This problem is solved using a simple OLS matrix solution:

$$\hat{B} = (X^T X)^{-1} X^T Y$$

Where the beta matrix is $\begin{Bmatrix} Intercept \\ Slope \end{Bmatrix}$, the X matrix is a column of ones and a column of the A[t] weights. Y is a vector of the Y[t]'s. This is really estimating the best slope an intercept from a non-linear trajectory that is already known.

Note that the Y[t] that this model is predicting is not in this OLS equation, only the prior time points are used for estimation of the intercept and the slope. This design simulates actually predicting future time points that have yet to occur.

Mean absolute error (MAE) was used as the measure of precision of the predicted number of offenses. MAE is simply the average absolute value of the difference between the predicted Y and the observed Y. This method gives less weights to outliers than methods that use sums of squares.

$$MAE = \frac{1}{n}\left|Y - \hat{Y}\right|$$

The latent growth mixture model (LGMM) utilized the two separate models estimated in the prior section for unobserved groupings of the data. To determine which model to use, the two OLS slope and intercepts based on the two sets of weights (A[t]'s) were both estimated. Then, maximum likelihood was used to determine which sample the individual most likely came from. (Based on the mean slope and intercepts estimated in the LGMM model). The likelihood function was:

$$L(\mu_{slope,}\mu_{icept}, \sigma_{slope}, \sigma_{icept} | \theta_{slope}, \beta_{icept}) = f(\theta; \mu_{slope,}, \sigma_{slope}) * f(\beta; \mu_{icept}, \sigma_{icept})$$

Where f() is the normal probability distribution function.

This gives two likelihood functions, one for each group. The two just simply need to be compared and the one with the higher likelihood chosen. The mean absolute error for each prediction model is presented in table 10. Table 11 shows the bias for each of these models.

The “mean” model outperformed the “unconstrained” model in precision, when predicting future time points for number of offenses at each age. This suggests that the unconstrained model, though it describes the data better than the mean model when all data is present (based on the SEM models in the prior section), it does a worse job at predicting unknown future events.

Table 10

Mean Absolute Error for Predicting Offenses: Holdout Sample N=12,546

			Model		
	Naïve	Baseline	Mean	Unconstrained	LGMM
Age					
13	0.37	0.361	0.217	0.337	0.335
14	0.52	0.551	0.361	0.518	0.513
15	0.69	0.759	0.568	0.748	0.72
16	0.81	0.851	0.742	0.894	0.835
17	0.87	0.841	0.793	0.899	0.86

In contrast to the precision, the mean model consistently under predicted future offending events. At later time points the bias was around .5. The unconstrained model under predicted offending events as well, but for most time points the bias was less than .1. Assuming the bias is consistent, the mean model could probably be drastically improved if time dependent intercepts were added (and these could be estimated by simply freeing up the intercepts on the SEM model, though one would still need to be fixed for identification purposes).

Table 11

Bias for Predicting Offenses:
Holdout Sample N=12,546

			Model		
	Naïve	Baseline	Mean	Unconstrained	LGMM
Age					
13	0.031	0.001	-0.165	-0.009	0.0001
14	0.001	-0.005	-0.268	-0.010	-0.009
15	-0.079	-0.003	-0.445	-0.012	-0.004
16	-0.091	-0.002	-0.564	-0.060	0.001
17	0.071	-0.01	-0.515	-0.130	-0.007

Post-Hoc Analyses

Though not originally hypothesized, due to the poor model fit and poor predictive utility of the latent growth model, an empirically determined residualized change model was examined. In this model, all time points were predicted by each previous time point. The model for each time point was allowed to have an intercept. This model was just identified in both the mean structure and the parameter estimates.

$$Y[t] = B_0 + B_1 Y[t-1] + B_2 Y[t-2] \dots$$

Because it was just identified, there was no model fit for this structural equation model. But an examination of the parameter estimates revealed that almost every time point was significantly predicted by just the previous two time points and the intercept. This suggests for future studies, that though much less elegant, a residualized change model where each time point is predicted by the previous two time points and an intercept may adequately describe the data. It is more than likely that the B parameters capitalize on chance to a large degree and may not be estimated consistently from dataset to dataset. (Which would make them poor candidates for prediction models).

Cross Validation of Unconstrained Model

Table 12

Bayesian Estimation: Unconstrained Growth Model Predicting Number of Offenses at Each Age (Holdout vs. Estimation Sample)

Parameter		Estimation	Holdout
Means			
	Intercept	0.011*	-0.002
	Slope	0.651*	0.673*
Variances			
	Intercept	0.008*	1.590*
	Slope	0.307*	0.352*
Covariance			
Slope and Intercept		0.002*	0.015
Slope Weights			
	Age 9	0†	0†
	10	0.023*	0.006*
	11	0.053*	0.043*
	12	0.156*	0.127*
	13	0.337*	0.303*
	14	0.571*	0.545*
	15	0.916*	0.886*
	16	1.114*	1.100*
	17	1†	1†

†Parameters fixed to scale model

*95% Credible Interval did not include zero

Holdout Model Fit: ppp=.00, DIC= 2,277

The unconstrained model was fitted using the holdout data to provide for cross validation of the parameter estimates (shown in Table 12). It was notable the intercept in the holdout sample was not significantly different from zero. All of regression weights from the slope were within the bootstrap estimates (table 5) with the exception of age 10. The estimate in the holdout sample was significantly below the 95% CI from the bootstrap. This suggests that the earlier age parameters may be more sample dependent than other parameters in the model. Also, the variance for the intercept in the holdout sample was several times larger than the one estimated in the previous sample. The parameter on age 16 was not only different from zero, but it was also different from 1, suggesting that the peak at age 16 with a decrease to age 17 is not a sample dependent phenomenon.

The predictive utility of this unconstrained model was similar to the original estimation sample (see table 13). The MAE values were greater than the ones predicted by the mean, but the bias was similarly small. This also would not function as a good predictive model for offending.

Table 13

Predicting the Estimation Sample Using the Estimated Weights From the Holdout Sample

	MAE	Bias
Age		
13	0.36	0.007
14	0.54	0.017
15	0.76	-0.009
16	0.91	-0.053
17	0.92	-0.11

Discussion

From these results, it would appear that a latent growth curve model is not necessarily the best way to *predict* future offending behavior. But what we can learn from this model is that there is good support for the idea that the age-crime curve is not just a group phenomenon, but an individual phenomenon. In other words, Moffit originally thought that the age crime curve was something that occurred because more individuals began offending during the middle of adolescence, but that during an individual's active offending period, that offending is relatively constant. What the "unconstrained" model tell us is that *for an individual* offending generally increases and then decreases through adolescence. In other words, there is something like an age-crime curve for each person.

The latent growth mixture modeling adds a more nuanced version of this individual age crime curve. This model shows us that 66% of the general population has a roughly equal chance of offending during the course of their adolescence. And they are probably only going to offend once and then never again. These youth, apart from adolescent limited youth, are "one timers," but they have roughly the same probability of offending at any age. This is in contrast to the idea of adolescent limited youth, who offend just during middle-late adolescence.

The second group, make up about a third of the general offender population. These are the individuals who offend multiple times and increase up to age 16 and then decrease. These are the offending youth who really influenced the general model to show an individual age crime curve. Based on the mixture modeling, it appears that these frequent offending youth really make up a smaller proportion of the overall population, but because they offend so much more than the "one timers" (they peak at almost two offenses per year) they heavily influence the general model.

Surprisingly, this study found that the "naïve" model, or the model that ignores the age of each offense, is not drastically worse than models that take into account the age of each offense. This finding could be due to the fact that this sample contains so many of the "one time" offenders identified by the mixture model. Nonetheless, there is no evidence that using models that just control for age as a linear covariate will result in findings that are drastically biased, but these models will not improve prediction much beyond guessing the mean either.

It should be noted that structural equation model fit does not necessarily measure what model will best predict future offending events. This is because model fit is measuring how well the model reproduces *all* of the relationships in a given data set. For predicting offending events, certain relationships cannot plausibly be used (for example, the causal path from age 17 to age 9).

Overall, models that just look at number of offenses at each age may be too simplistic to capture what is really causing offending that persists, versus offending that desists. Models that take more variables into account are likely needed to better predict future offending events. Future directions for research might include looking at the stability across samples of residualized change scores. Also, more sophisticated models that take into account types of offenses at each age may still leave a more promising avenue for latent growth modeling of offending events.

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