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Population Heterogeneity in the Salience of Multiple Risk Factors for Adolescent Delinquency

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Abstract

Purpose—To present mixture regression analysis as an alternative to more standard regression analysis for predicting adolescent delinquency. We demonstrate how mixture regression analysis allows for the identification of population subgroups defined by the salience of multiple risk factors.

Methods—We identified population subgroups (i.e., latent classes) of individuals based on their coefficients in a regression model predicting adolescent delinquency from eight previously established risk indices drawn from the community, school, family, peer, and individual levels. The study included $N = 37,763$ tenth-grade adolescents who participated in the Communities that Care Youth Survey. Standard, zero-inflated, and mixture Poisson and negative binomial regression models are considered.

Results—Standard and mixture negative binomial regression models are selected as optimal. The five-class regression model is interpreted based on the class-specific regression coefficients, indicating that risk factors have varying salience across classes of adolescents.

Conclusions—Standard regression shows that all risk factors are significantly associated with delinquency. Mixture regression provides more nuanced information, suggesting a unique set of risk factors that are salient for different subgroups of adolescents. Implications for the design of subgroup-specific interventions are discussed.

Keywords

adolescence; risk factor; adolescent delinquency; mixture regression analysis; subgroup analysis; differential effects

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Delinquency has been associated with poor outcomes such as alcohol and drug abuse, mental health problems, and chronic antisocial behavior (1–4). Prevention efforts have targeted well-documented risk factors across five domains: community, school, family, peer, and individual (5–10). Although these programs have some evidence of effectiveness, it is unlikely that the same risk and protective factors are salient for all individuals. For example, Cleveland and colleagues (11) found that adolescents' family protection score was significantly associated with lower substance use only for adolescents attending schools characterized by high average family protection scores, suggesting that family factors were less protective in higher risk school contexts. Thus it is important to understand population heterogeneity in the salience of risk and protective factors (i.e., strength and significance of regression coefficients) (12–13). The role of these factors in the onset and escalation of delinquency may vary across adolescents (14–15). Although several studies have uncovered latent subgroups of individuals based on the heterogeneity in their offending patterns across time (e.g., 16–17), fewer studies have examined the heterogeneity in salience of particular risk and protective factors associated with delinquency subgroups during adolescence. This paper presents mixture regression analysis as an alternative to more standard regression analysis. Mixture regression analysis allows for the examination of population heterogeneity in associations between risk factors and problem behavior by identifying population subgroups within which different risk factors may be associated with delinquency. The approach also can accommodate the large number of non-delinquent individuals (i.e., preponderance of zeros) within general population samples.

Modeling Low-Incident Count Outcomes

Behaviors such as delinquency are typically assessed with count variables indicating the number of times the behavior occurs over some time period. In a general population, the resulting data are characterized by *excess zeros*, given that much of the population does not engage in the behavior, and *over-dispersion*, where the variance substantially exceeds the mean (often because a small number of individuals engage in extreme levels of the behavior). Several closely related models are available for predicting a count variable, most notably Poisson regression, where the mean and variance are assumed to be equal, and negative binomial (NB) regression, which adds an over-dispersion parameter to the Poisson model to accommodate violations of this assumption. These models can be extended to zero-inflated Poisson (ZIP) and zero-inflated NB (ZINB) regression to accommodate excess zeros; these models posit two types of individuals who report zero delinquent acts: those who are non-delinquent, and those who have the potential to engage in delinquency but report zero acts during that time.

Importantly, coefficients in Poisson and NB regression are assumed to apply to all individuals uniformly. These methods can be extended to mixture regression models, which allow examination of population heterogeneity (18–20). Conceptually, mixture regression analysis posits that two or more underlying subgroups exist such that those subgroups differ in their regression coefficients. For example, suppose there are two subgroups of adolescents: adolescents for whom parental monitoring is a critical risk factor for delinquency, and adolescents for whom attitude toward delinquency, but not parental monitoring, is a risk factor. Such subgroups, defined by the risk factors salient to each, could not be identified with linear regression. We posit that in the national population of adolescents, heterogeneity exists in the role that risk factors play in delinquency; thus, we use mixture regression analysis to identify subgroups that vary in mean delinquency counts and salience of risk factors.

Mixture Regression Models

Mixture regression analysis is analogous to latent class analysis (21), in that latent subgroups are identified based on observed variables (i.e., indicators). In latent class analysis, the indicators are observed categorical variables; in mixture regression analysis they are regression coefficients—specifically, the intercept and slope coefficients from the model (e.g., linear regression). The behavioral science literature contains several applications of these models (e.g., 22–24). An overview by Dyer, Pleck, and McBride (25) that focuses on continuous outcomes provides an excellent introduction to this approach as an alternate framework that does not rely on tests of interactions between predictors and observed moderators.

The extension of regression models for count outcomes to a mixture modeling framework has seldom been applied in behavioral science. One exception is a study of heterogeneity in the salience of adolescent risk factors for sexual risk behavior in adulthood (26); school connectedness was found to be equally salient across subgroups, but early sexual debut, heavy episodic drinking, and consequences of intercourse were more salient among adolescents in lower-risk groups.

The Current Study

The current study considers various models for predicting adolescent delinquency. We focus on adolescents in the tenth grade, when delinquent behavior tends to increase (2). Delinquency, an over-dispersed count variable with excess zeros, is predicted from eight established risk indices occurring at the individual, peer, family, school, and community levels. Four standard regression models and several regression mixture models for count outcomes are considered. The advantages of mixture regression analysis both to accommodate the distribution of delinquency and to examine heterogeneity in the salience of risk factors are demonstrated. Differences in implications of results from standard and mixture regression analysis are discussed.

Methods

Procedure

This study uses data from the Communities that Care Normative Database (27), which monitors adolescent problem behavior and a broad set of risk and protective factors for that behavior via the CTC Youth Survey (CTC-YS). In 2000 and 2002, over 300,000 students from 23 states in grades 6–12 self-administered the CTC Prevention Needs Assessment, a cross-sectional, school-based survey designed to collect data on the students' levels of risk and protection within their peer group, family, school, and community (see 28–30). Students also answered questions about substance use and delinquent behavior. School-level variables from the National Center for Education Statistics and community-level variables from the 2000 U.S. Census were included to create sample weights that ensured national representativeness with respect to gender, grade, ethnicity, urbanicity, and socioeconomic status.

Of the 56,462 adolescents in tenth grade, 37,763 with complete data on all variables used here were included in the current study. A comparison of the adolescents retained for this analysis to those removed indicates that females comprised a significantly higher portion of the retained individuals (53.6% versus 47.2%; chi-square=193.9, 1 df, $p<.0001$). However, the two groups did not differ in terms of racial group, with 74.6% and 74.2% white adolescents in the retained and removed subgroups, respectively (chi-square=0.3, 1 df, $p=0.34$). The final sample consisted of 53.6% female, 74.6% White, 7.2% African American, 6.5% Hispanic, and 11.7% other racial groups. Language spoken at home was

93.4% English, 3.6% Spanish and 2.7% other. The average proportion of students in the participants' schools who qualify for the Reduced Lunch Program is 5.3%. Over 73% report living in a city, town, or suburb, compared to 22.8% in the country and 4.2% on a farm. Approximately 19% report that crime and/or drug selling describes their neighbourhood.

Measures

Delinquency—The delinquency measure was created from the following questions: “How many times in the past year (12 months) have you: (1) Been suspended from school? (2) Sold illegal drugs? (3) Stolen or tried to steal a motor vehicle such as a car or motorcycle? (4) Been arrested? (5) Attacked someone with the idea of seriously hurting them? (6) Been drunk or high at school?” Original items included responses 0=Never, 1=1 or 2 times, 2=3 to 5 times, 3=6 to 9 times, 4=10 to 19 times, 5=20 to 29 times, 6=30 to 39 times, and 7=40 or more times. Developers of the CTC-YS recoded these variables to reflect estimated number of occasions as 0.0, 1.5, 4.0, 7.5, 14.5, 24.5, 34.5, and 40.0 for response categories 1 through 7, respectively. To create the count outcome for this study, the estimated number of occasions for the six behaviors was summed and rounded to the nearest integer.

Aggregated risk indices—The validity and reliability of the CTC-YS scales have been established across population groups in the United States (29). Eight previously established, aggregated indices of risk for adolescent behavior problems were included as predictors in the regression models (31). These indices, described in Table 1, represent key aspects of risk across five ecological levels: community, school, family, peer, and individual. Protective factors were reverse-coded such that higher scores correspond to greater risk (see 28). Thus, we refer to all scores as risk indices. Index scores were standardized ($M=0$, $SD=1$) so that the relative strength of regression coefficients could be compared, and reliability of the indices was calculated for the present sample.

Two indices represent risk at the community level: *Low Community Cohesion* ($\alpha=.56$), *High Community Drugs/Firearms Risk* ($\alpha=.61$). One represents risk at the school level: *Low School Opportunities for Prosocial Involvement* ($\alpha=.76$). Two represent risk at the family level: *Low Family Cohesion* ($\alpha=.86$), *High Family Risk* ($\alpha=.73$). One represents risk at the peer level: *Antisocial Peers* ($\alpha=.71$). Two represent risk at the individual level: *Antisocial Behaviors and Attitudes* ($\alpha=.84$), *Risky Behaviors* ($\alpha=.76$).

Analytic Strategy

Standard regression for a count outcome—The goal of this analysis was to estimate population-average associations between eight continuous risk indices and delinquency. We first employed a standard linear regression model where the outcome (number of past-year delinquent acts) was specified as a count variable. Based on an examination of its distribution (see Figure 1), we considered the following models: Poisson, ZIP, NB, and ZINB regression. Models included here specify risk indices as covariates only in the count part of the ZIP and ZINB models and therefore model how risks predict level of delinquency only for delinquent adolescents. For each of the four models, the number of past-year delinquent acts was expressed as a function of the eight risk indices (see Table 1 for definitions and correlations). Results yield estimated associations between each risk index and delinquent behavior, controlling for the other risk indices.

Model selection from among these parameterizations was conducted using fit indices (AIC and BIC; lower values correspond to better balance between fit and parsimony). All four models can be fit in SAS using PROC GENMOD or PROC FMM (32) (see Appendix for syntax for the less familiar PROC FMM).

Mixture regression for count outcome—The goal of the next analysis was to identify population subgroups defined by their average delinquency, variability in delinquency (i.e., dispersion parameter), and regression coefficients for the eight risk indices. In other words, we sought to identify population subgroups that differed in mean number of delinquent acts, variability in number of delinquent acts across individuals in the subgroup, and—importantly—the salience of the eight risk indices for predicting delinquency. We considered mixture Poisson models and mixture NB models, each with the number of latent classes equal to two, three, and so on, until the number of classes was too large to be identified. Mixtures of ZIP and ZINB are not considered, because these models are mixture models themselves; their extension to mixtures of mixtures is not yet well understood. In each mixture regression model, two sets of parameters were estimated: the proportion of individuals in each class (i.e., class membership probabilities) and the class-specific regression coefficients. For mixture NB models, a third set is estimated: the class-specific dispersion parameters. Within each class, regression coefficients hold the same interpretation as those in the corresponding standard regression.

To conduct the mixture Poisson and mixture NB regression, we first determined the optimal number of classes. Model selection was conducted using a combination of the AIC, BIC, and interpretability. The following parameters were allowed to vary across classes:

- *intercept* (i.e., estimated mean delinquency count for individuals with population-average scores on all risk indices),
- *regression coefficients for risk indices* (i.e., estimated associations between risk indices and delinquency, holding other indices constant), and
- *dispersion parameter*.

SAS PROC FMM (32) was used to estimate all mixture regression models (see Appendix for syntax).

Results

The distribution of the outcome, shown in Figure 1, is characterized by excess zeros, over-dispersion, and right skew ($\mu=5.09$, $SD=16.7$, range 0–240). These characteristics are common in behavioral research and will be addressed herein.

Standard Regression: Overall Associations Between Risk and Delinquency

The top panel of Table 2 shows fit information for the four models under consideration. Extending the Poisson model to accommodate the excess zeros substantially improved fit ($-2\log L$ decreased from 404,307 to 287,742); however both the NB and ZINB fit better than either Poisson model. Because the NB and ZINB fit the data equally well ($-2\log L$ of 116,676 for each) and the NB model had the minimum AIC and BIC, we chose the more parsimonious NB regression model.

The first column of coefficients in Table 3 shows results from the standard NB regression analysis, in which the total number of delinquent acts was expressed as a function of an intercept, a dispersion parameter, and eight risk indices. The intercept, 0.309, corresponds to the log of the mean delinquency count among all adolescents when all predictors in the model are set to zero. In other words, for adolescents with average levels on all risk indices, the expected number of delinquent acts in the past year was $e^{0.309}=1.36$. A positive dispersion parameter (4.418) indicates that the outcome was over-dispersed. All risk indices were significantly and positively associated with the number of delinquent acts in the overall population. These coefficients reflect the association between each risk index and delinquency count, after adjusting for other predictors in the model. For example, a one-

standard-deviation increase in family risk corresponds to $e^{0.305}=1.36$ times more delinquent acts, holding all other predictors constant. Associating with antisocial peers had the largest coefficient, corresponding to $e^{0.823}=2.28$ times more delinquent acts for every one-unit increase.

Mixture Regression: Class-Specific Associations

The bottom panel of Table 2 shows model fit information for the ten mixture regression models under consideration: mixture Poisson and mixture NB, each with two through six latent classes. Models with seven latent classes were not identified. Not surprisingly, every mixture NB model provided superior fit to any mixture Poisson model. Among the NB models, the improvement in fit was substantial through five latent classes but very small when increasing from five to six latent classes ($-2\log L$ decreased from 112,888 to 112,835). The AIC is nearly identical for the 5- and 6-class models, and the BIC supports the more parsimonious 5-class model; we selected this as our final model.

The five right-most columns in Table 3 present results from the mixture NB regression model with five latent classes. Analogous to standard regression, the total number of delinquent acts was expressed in terms of a class-specific intercept, a class-specific dispersion parameter, and class-specific coefficients for eight risk indices. In addition, class membership prevalences were estimated.

The first class, labeled *Non-Delinquents*, comprised 57.7% of the sample. Adolescents in this class had a low mean delinquency count ($e^{-2.590}=0.08$ for adolescents with average scores on all risk indices); therefore, the dispersion parameter was the highest among all classes (2.202) to allow for non-zero variance in the delinquency count. Peer and individual risk indices were more strongly related to delinquency for the Non-Delinquents compared to any other class, with a one-unit increase in Antisocial Peers, Antisocial Attitudes, and Risky Behaviors corresponding to $e^{1.024}=2.78$, $e^{0.923}=2.52$, and $e^{0.971}=2.64$ times more delinquent acts, respectively (see Table 3).

The second class, labeled *Low Delinquency/Community Cohesion Risk*, comprised 8.3% of the sample. Adolescents in this class had a low mean delinquency count ($e^{0.784}=2.19$ for those with average scores on all risk indices), and the dispersion parameter was near zero (0.038), indicating that the mean and variance were essentially equal. Community Cohesion was a significant predictor only in this class ($e^{0.083}=1.09$; see Table 3).

The third class, labeled *Low Delinquency/Multilevel Risk*, comprised 28.6% of the sample and was characterized by a low mean delinquency count ($e^{0.103}=1.11$ for adolescents with average scores on all risk indices). The dispersion parameter was 1.328. Significant risk was conferred at all five levels, and the pattern of associations for this group of adolescents was most similar to those in the overall sample, described by the standard NB regression model (see Table 3).

The fourth class, labeled *Moderate Delinquency/Community, Peer, Individual Risk*, comprised 4.3% of the sample. Adolescents in this class with average scores on all risk indices had a mean delinquency count of $e^{2.134}=8.45$. The dispersion parameter was 0.599. Only the most distal (community) and the most proximal (peer and individual) risk indices were significantly associated with delinquency. Significant predictors included Community Drugs/Guns, Antisocial Peers, Antisocial Attitudes, and Risky Behaviors (see Table 3). Among all classes, the coefficient for Community Drugs/Guns was the strongest in this class.

The fifth class, labeled *High Delinquency/School, Peer Risk*, was the smallest (1.1%) and had the highest mean delinquency ($e^{3.798}=44.63$ for adolescents with average scores on all risk indices). The dispersion parameter was 0.173. Only two risk indices were modestly related to delinquency: School Prosocial and Antisocial Peers. A one-unit increase on the scale for low opportunities for prosocial involvement at the school corresponded to $e^{0.091}=1.09$ times more delinquent acts, and a one-unit increase on the antisocial peers scale corresponded to $e^{0.168}=1.18$ times more delinquent acts (see Table 3). This is the only class in which individual risk was unrelated to delinquency.

Discussion

This study adds to the limited research that uses mixture regression to better understand heterogeneity in risk for behavioral outcomes (24, 26). Specifically, it presents mixture regression as an alternative to more standard regression in order to 1) examine population heterogeneity in associations between risk factors and problem behavior, which has possible implications for subgroup-specific mechanisms to target in interventions, and 2) accommodate excess zeros in reported delinquency.

Results from the standard regression confirm previous findings that community, school, family, peer, and individual factors confer risk in the overall population of adolescents, with individual and peer factors most strongly and consistently related to delinquency (e.g., 33–35). Results from the mixture regression align with past research on non-delinquent, low, moderate and high-level delinquency subgroups (e.g., 17) and provide new insight into the relative salience of risk factors for population subgroups. Because peer and individual risks were significantly associated with delinquency across nearly all classes, our results provide further support for universal programs like Life Skills Training, which targets individual youth competencies and peer-pressure resistance skills as mediators in the prevention of delinquency (36–37). Our results also inform those risks that may be best targeted among certain types of individuals (e.g., community and family cohesion were each salient for just one class). For instance, Functional Family Therapy, which was designed to reduce delinquency by improving family cohesion and reducing family conflict (38), or a multi-level intervention like Fast Track, which was designed to provide both individual youth skill building and targeted family services (39), may be most effective among youth in the Low Delinquency/Multilevel Risk class where family cohesion was a salient predictor.

The mixture regression approach demonstrated here resulted in a more comprehensive understanding of factors that may inform the tailoring of prevention programs for different population subgroups, thus leveraging resources more effectively (40). An interesting finding was the low salience of all risk factors for the class characterized by high delinquency. This may be due partially to a restriction of range; if all individuals in this class are exposed to very high levels of individual risk, the coefficient may not reach statistical significance. It is possible that this class reflects a small group of individuals known as “life-course persistent” or “chronic offenders” for whom neurological or cognitive impairments prevent them from desisting from delinquent behaviors as they transition to adulthood (2). The underlying population subgroups identified in this study are not only characterized by their delinquent behavior, but are *defined* by the multiple processes underlying that behavior.

Because the entire regression model (i.e., intercept, coefficients for risk factors, and dispersion parameter) can vary across classes, this approach can provide a holistic understanding of the different processes that likely underlie delinquency. The prevention implications of this model are explicit: within a class, the significant regression coefficients indicate which risk factors hold promise for intervention. Individual characteristics can be

incorporated as predictors of class membership to better understand the composition of classes.

Our study has several limitations. First, the data were cross-sectional, thus the effects of risk factors cannot be interpreted as causal. Second, other potentially important risk factors (e.g., cognitive impairment) were not included and warrant further investigation. Third, individuals with missing data on one or more of the constructs studied here were deleted despite the fact that they may have differed in important ways from those with complete data. Because of this, sample weights could not be used and therefore results are not nationally representative. Multiple imputation in the context of mixture regression analysis is an important area for future research; this approach may introduce complications such as determining the number of latent classes across imputations. Fourth, community risk indices had relatively low reliability. Despite the attenuation of effects caused by this, coefficients in both standard and mixture regression models were statistically significant. Fifth, although the large sample size is a substantial strength, because of the high statistical power even small coefficients were significant.

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Definitions of Acronyms

CTC-YS	Communities that Care – Youth Survey
NB	Negative binomial
ZINB	Zero-inflated negative binomial
ZIP	Zero-inflated Poisson

Appendix

SAS syntax used to estimate standard negative binomial regression model:

```
*Negative binomial regression model;
proc fmm data=ctc_data.ctc_recoded_nomiss;
model antsocl3r=comcoh comdraggun schprsoc famcoh famrisk antipeer
attitude riskbeh / dist=negbin;
title 'MODEL NB';
run;
```

SAS syntax used to estimate standard negative binomial regression model:

```
*Mixture negative binomial regression model, 5 classes;
proc fmm data=ctc_data.ctc_recoded_nomiss;
```



```

model antsocl3r=comcoh comdrsgun schprsoc famcoh famrisk antipeer
attitude riskbeh / dist=negbin k=5;
output out=MNB class=ML;
title 'MODEL MIX-NB-5';
run;

```

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Implications and Contribution

Risk factors for adolescent delinquency, which may exist in individual, peer, family, school, and community levels, are well documented. However, they may not be equally salient for all individuals. We present an approach to identify subgroups of adolescents based on which risks are most salient and describe implications for prevention.

Figure 1.
Empirical distribution of number of delinquent acts in past year ($n = 37,763$)

Table 1

Descriptions and Correlations Among Risk and Protective Factors

Risk Index and Corresponding Subscales	Correlations Among Risk Indices							
	2	3	4	5	6	7	8	
1. Community Cohesion								
Neighborhood attachment (reversed); Community disorganization; Community rewards for prosocial involvement (reversed)	.32	.37	.41	.29	.28	.33	.30	
2. Community Drug/Firearm Availability and Norms								
Laws and norms about drug use and firearms; Perceived availability of drugs and firearms		.34	.33	.53	.48	.53	.50	
3. School Support for Prosocial Activities								
School opportunities for prosocial involvement (reversed); School rewards for prosocial involvement (reversed); Low school commitment			.44	.31	.35	.48	.43	
4. Family Cohesion								
Family attachment (reversed); Family opportunities for prosocial involvement (reversed); Family rewards for prosocial involvement (reversed); Family supervision (reversed); Family discipline (reversed)				.33	.31	.48	.44	
5. Family Risk								
Parental attitude toward alcohol, tobacco, and other drug use; Parental attitudes toward antisocial behavior; Family history of antisocial behavior					.53	.58	.52	
6. Antisocial Peers								
Friends' delinquent behavior; Friends' use of drugs; Gang involvement; Peer rewards for antisocial behavior						.60	.57	
7. Antisocial Attitudes								
Perceived risks of drug use; Attitudes toward antisocial behavior; Attitudes toward alcohol, tobacco, and other drug use; Belief in moral order							.75	
8. Risky Behaviors								
Rebelliousness; Social skills (reversed); Sensation seeking								

Table 2
Model Fit Information for Competing Regression Models for Count Outcome with Eight Risk Indices as Predictors ($n = 37,763$)

Model Label	Model Description	Number of Parameters	-2 Log Likelihood	AIC	BIC
<i>Standard Regression Analysis</i>					
P	Poisson	9	404,307	404,325	404,402
ZIP	Zero-inflated Poisson	10	287,742	287,762	287,848
NB	Negative binomial	10	116,676	116,696	116,781
ZINB	Zero-inflated negative binomial	11	116,676	116,698	116,792
<i>Mixture Regression Analysis</i>					
MIX-ZIP(2)	Mixture Poisson – 2 classes	19	170,021	170,059	170,221
MIX-ZIP(3)	Mixture Poisson – 3 classes	29	138,512	138,570	138,818
MIX-ZIP(4)	Mixture Poisson – 4 classes	39	126,932	127,010	127,343
MIX-ZIP(5)	Mixture Poisson – 5 classes	49	121,332	121,430	121,849
MIX-ZIP(6)	Mixture Poisson – 6 classes	59	119,896	120,014	120,517
MIX-NB(2)	Mixture negative binomial – 2 classes	21	113,848	113,890	114,070
MIX-NB(3)	Mixture negative binomial – 3 classes	32	113,325	113,389	113,662
MIX-NB(4)	Mixture negative binomial – 4 classes	43	113,166	113,252	113,619
MIX-NB(5)	Mixture negative binomial – 5 classes	54	112,888	112,996	113,457
MIX-NB(6)	Mixture negative binomial – 6 classes	65	112,835	112,965	113,520

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion. Bold font signifies selected models.

Table 3
Standard and Mixture Regression Models Predicting Delinquency Count as a Function of Eight Risk Indices ($n = 37,763$)

Mixture Negative Binomial Regression						
Estimated Coefficient (Exponentiated Coefficient)	Standard Negative Binomial Regression	Non- Delinquent	Low Delinq./ Community Cohesion Risk	Low Delinq./ Multilevel Risk	Moderate Delinq./ Community, Peer, Individual Risk	High Delinq./ School, Peer Risk
Percent Estimated in Class	n/a	57.7%	8.3%	28.6%	4.3%	1.1%
Intercept (Mean Delinquency Count)	0.309** (1.36)	-2.590** (0.08)	0.784** (2.19)	0.103 (1.11)	2.134** (8.45)	3.798** (44.61)
Dispersion Parameter	4.418 (n/a)	2.202 (n/a)	0.038 (n/a)	1.328 (n/a)	0.599 (n/a)	0.173 (n/a)
Community Risk						
Community Cohesion	0.028* (1.03)	-0.036 (0.96)	0.083** (1.09)	0.045 (1.05)	-0.024 (0.98)	0.010 (1.01)
Community Drug/Guns	0.143** (1.15)	0.288** (1.33)	-0.008 (0.99)	0.238** (1.27)	0.272** (1.31)	0.021 (1.02)
School Risk						
School Prosocial	0.141** (1.15)	-0.143* (0.87)	-0.048 (0.95)	0.185** (1.20)	0.033 (1.03)	0.091** (1.10)
Family Risk						
Family Cohesion	0.112** (1.12)	0.031 (1.03)	-0.009 (0.99)	0.125** (1.13)	0.059 (1.06)	0.025 (1.03)
Family Risk	0.305** (1.36)	0.350** (1.42)	0.262** (1.30)	0.420** (1.52)	0.109 (1.12)	0.050 (1.05)
Peer Risk						
Antisocial Peers	0.823** (2.28)	1.024** (2.78)	0.435** (1.54)	0.930** (2.53)	0.712** (2.04)	0.168*** (1.18)
Individual Risk						
Antisocial Attitudes	0.408** (1.50)	0.923** (2.52)	0.152** (1.16)	0.578** (1.78)	0.322** (1.38)	-0.081 (0.92)
Risky Behaviors	0.436** (1.55)	0.971** (2.64)	0.254** (1.29)	0.524** (1.69)	0.237** (1.27)	0.008 (1.01)

* $p < .05$;

** $p < .01$

Note. Coefficients significant at $p < .05$ for risk indices marked in bold to facilitate comparisons across models and across classes.