

Exploring Delinquency in High Risk Students using Longitudinal Zero-Inflated Poisson Bayesian models

Christopher David Desjardins, Chu-Ting Chung, and Jeffrey D. Long

Department of Educational Psychology, University of Minnesota, Minneapolis, Minnesota



UNIVERSITY OF MINNESOTA

Introduction/Background

- ▶ Delinquency emerges in the lower grades, peaks in middle and high school, and declines in adulthood¹
- ▶ It has been associated with **poor parental supervision, violent parents, child abuse, low family income, peer delinquency and academic failure**²
- ▶ High risk students face additional stresses that may increase delinquency:
 - ▶ They experience higher parental distress, cumulative risk stress, depression, and higher exposure to adversity³
 - ▶ This heightened stress can carry over and **negatively impact achievement and behavior**
- ▶ Suspensions from school are one measure for assessing childhood delinquency
- ▶ Most studies have been cross-sectional or not accounted for correlations associated with repeated measurements or nesting of students in school
- ▶ How to deal with a longitudinal outcome measure were majority of the students have no suspensions?

Research Questions

- ▶ Does suspensions follow a similar growth trajectory to other delinquent behaviors and is there a risk gradient?
- ▶ Is there a development component to suspensions? Do trajectories and timing differ by gender and gender by ethnicity interactions?
- ▶ Do models that account for zero-inflation fit better than traditional Poisson models?

Methods

Sample

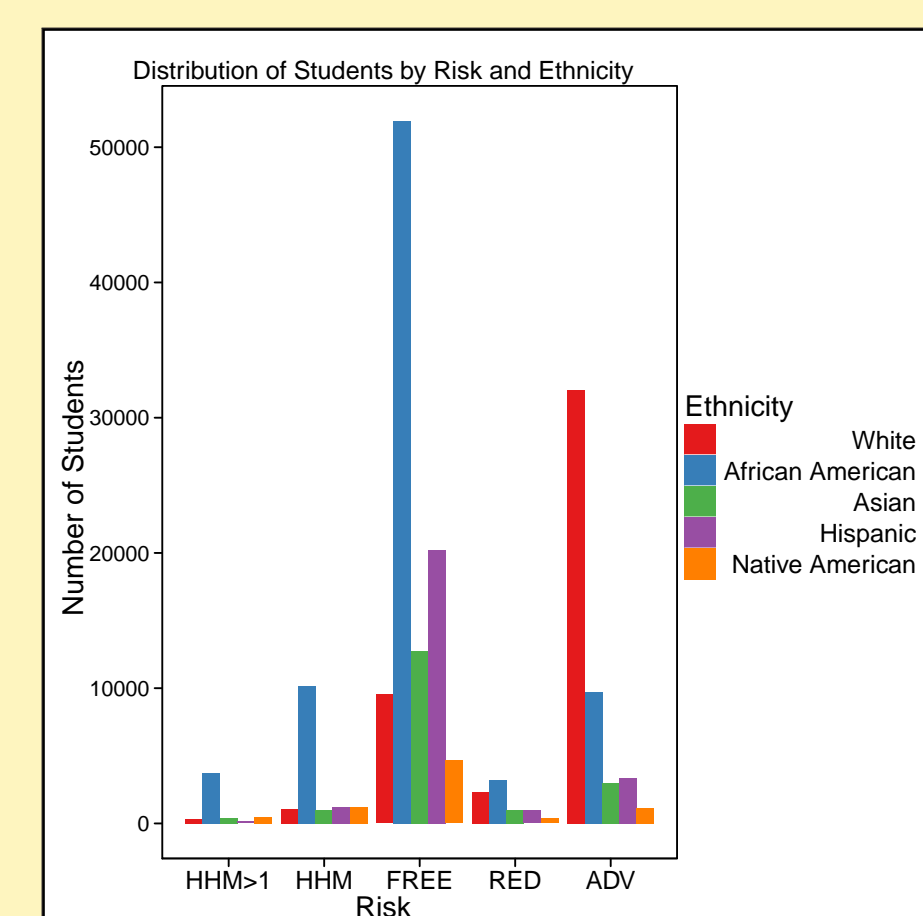
- ▶ Data were collected by Minneapolis Public Schools
 - ▶ **81,724** students in grades 1 - 12
 - ▶ **175,975** data points
 - ▶ All students included in study had complete data on the **independent variables**

Risk Classification

- ▶ **HHM > 1** - Students were homeless or highly mobile (HHM) more than once
- ▶ **HHM** - Students were HHM only once
- ▶ **FREE** - Students were on free lunch but not HHM
- ▶ **RED** - Students were on reduced-priced lunch but not HHM
- ▶ **ADV** - Neither HHM nor FREE or RED

Descriptives

- ▶ **127 schools examined**
- ▶ Males and females evenly distributed through risk groups
- ▶ **Special education ranges from 34% in HHM > 1 to 10% in ADV.**
- ▶ **86% of all data points are zeros.**
- ▶ 72%, in HHM > 1, 77% in HHM, 83% in FREE, 89% in RED, and 96% in ADV



Statistical Methods/Analysis

Zero-Inflated Poisson Models (ZIP)

- ▶ Poisson and ZIP Bayesian multilevel models were examined
- ▶ ZIP models are mixture models consisting of a zero-inflation and Poisson component
- ▶ Zeros arise from both components
- ▶ **Complex model**
 - ▶ Requires MCMC burn-in of 10,000 and 60,000 iterations to converge!
 - ▶ Estimates parameters for binomial (zero-inflated) and Poisson components
 - ▶ **Requires** specification of a prior on B-, G-, and R- structures
 - ▶ However, G-structure is fixed because residual can not be estimated with binomial models but R-structure highly susceptible to priors

Analysis: Question 1

- ▶ To answer question 1, ZIP multilevel quadratic models with covariate-intercept interactions were examined
- ▶ Included a school level effect (i.e. nesting of students within school).
 - ▶ Flat prior on B-structure ($\mu = 0; \sigma^2 = 1e10$)
 - ▶ Prior on G-structure was fixed
 - ▶ R-structure had a flat inverse-Wishart prior ($\nu = 1; V = 1$) with Cauchy parameter expansion ($\mu = 0; \sigma^2 = 25^2$)
- ▶ Compared growth curve to other delinquent behaviors and examined Bayesian confidence intervals and posterior models

Analysis: Question 2

- ▶ Examined timing and trajectories of males and females
 - ▶ If developmental, then females should have an earlier suspension crescendo
- ▶ Examined timing and trajectories of gender by ethnicity
 - ▶ If developmental, crescendo of Hispanic females should be first, followed by African American females

Analysis: Question 3

- ▶ Poisson and ZIP models
- ▶ Comparison of growth curves

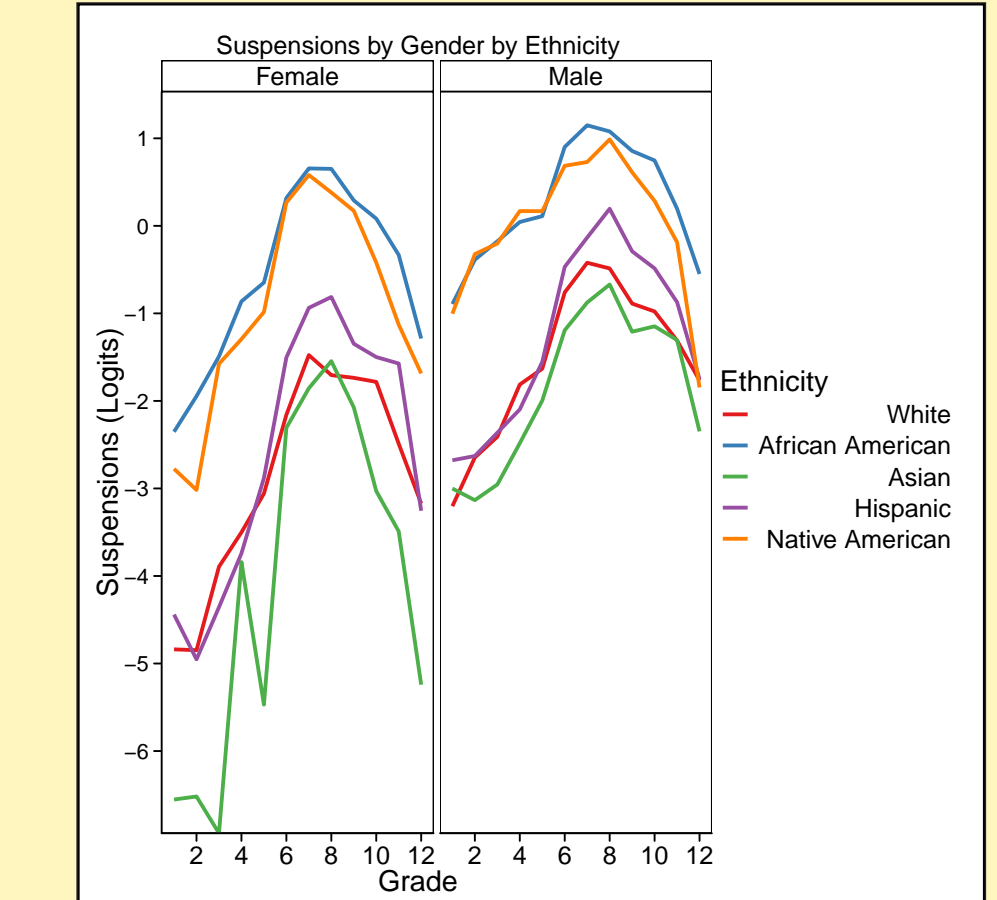
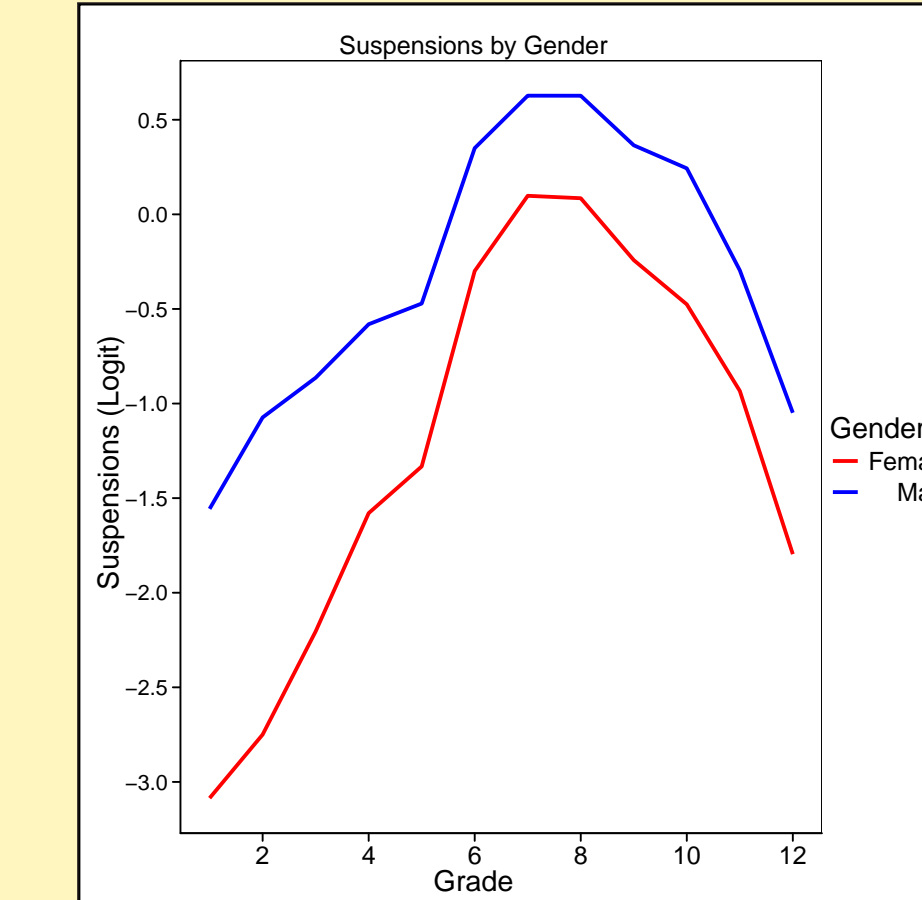
Results

Results: Question 1

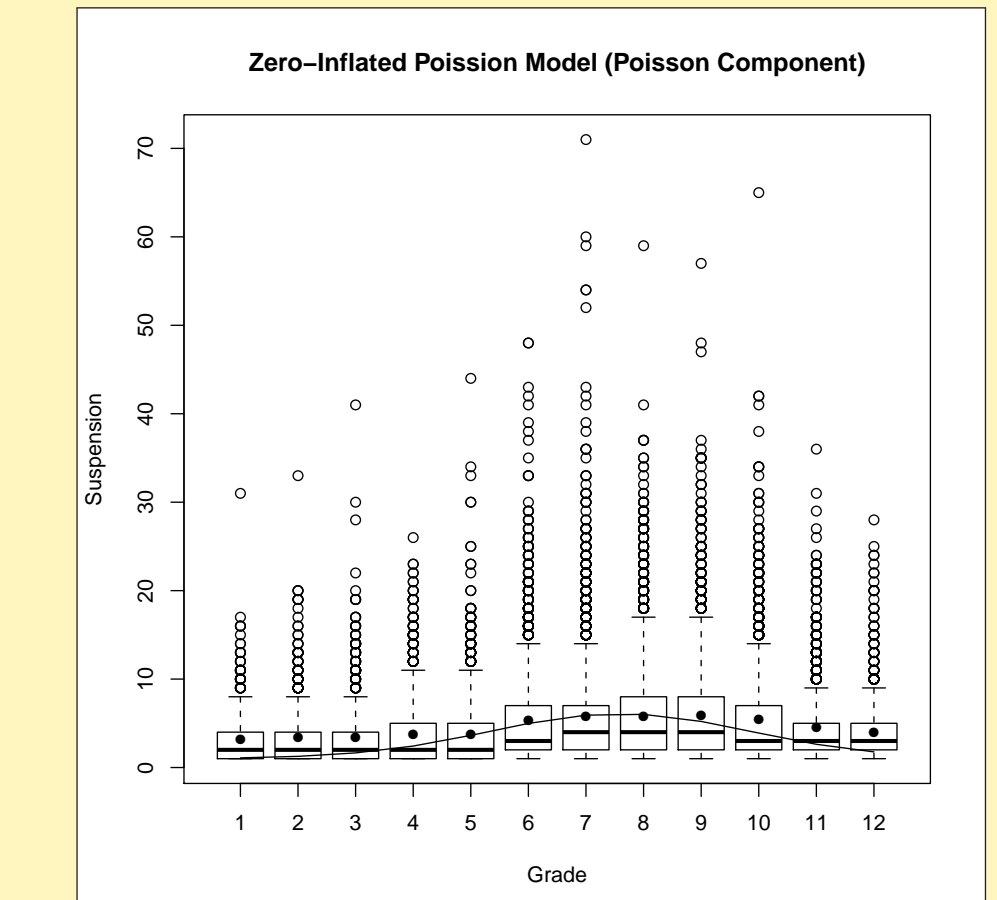
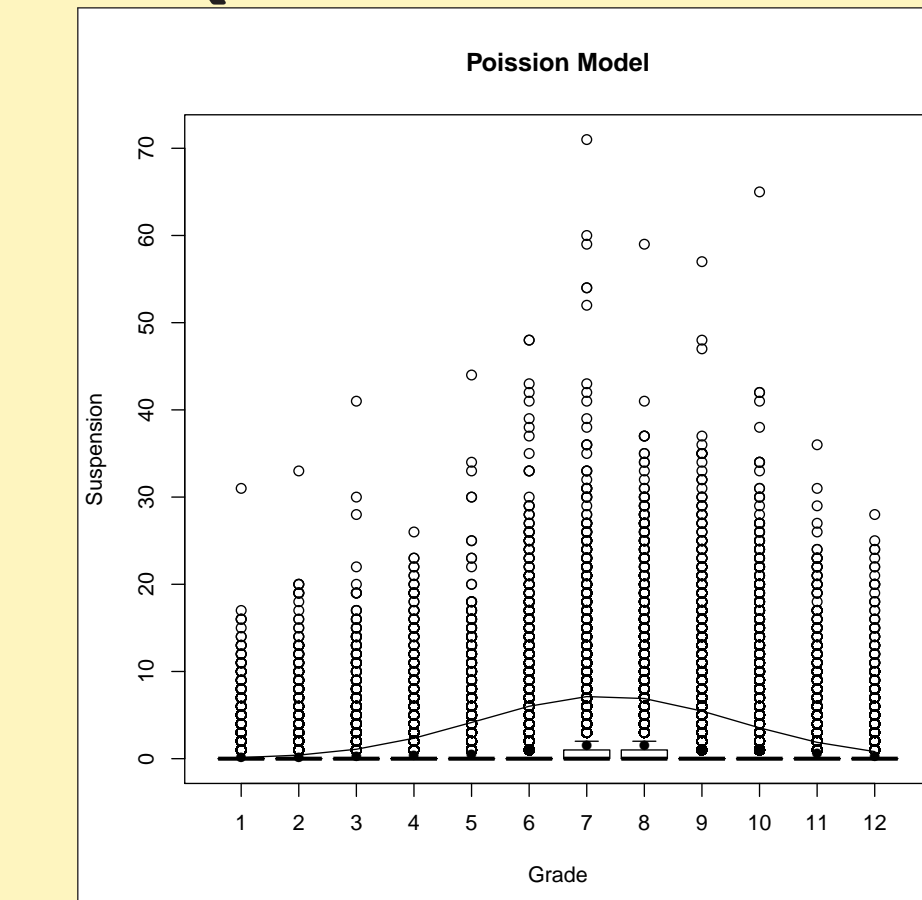
Parameter Estimates	Posterior Mode	95% Bayesian CI
HHM v. HHM > 1	-0.349	-0.456, -0.194
FREE v. HHM > 1	-0.606	-0.740, -0.491
RED v. HHM > 1	-1.127	-1.279, -0.946
ADV v. HHM > 1	-2.021	-2.15, -1.885
African American v. White	1.369	1.311, 1.475
Asian v. White	-1.404	-1.561, -1.302
Hispanic v. White	-0.114	-0.213, -0.013
Native American v. White	1.153	1.002, 1.252
Special Education	0.894	0.822, 0.938
Gender	1.032	0.979, 1.085
Grade	0.961	0.933, 1.002
Grade ²	-0.065	-0.067, -0.062

Results

Results: Question 2



Results: Question 3



Conclusion

- ▶ Suspension showed similar growth trajectory to other delinquent behaviors
 - ▶ However, timing was earlier than other behaviors
 - ▶ Driven by policy but influenced by puberty?
- ▶ There was no difference in timing of crescendo for gender and gender by ethnicity interactions
- ▶ The ZIP and Poisson models appear to show no differences?
 - ▶ **However, residual variance greater in Poisson than ZIP model and ZIP better predicts zeros!**
 - ▶ More posterior predictive checks required
- ▶ Both multilevel ZIP and Poisson required priors to converge, i.e. needed to use **Bayesian statistics**
 - ▶ Bayesian approaches widely accepted in other fields such as ecology and biostatistics
 - ▶ Can use sensitivity analysis to examine robustness of estimates under different priors
 - ▶ **How should we deal with prior specification?**
- ▶ Future simulation work comparing ZIP v. Poisson models under myriad of scenarios

References/Acknowledgements

- ¹Moffitt, T. (1993). Adolescence-limited and life-course-persistent antisocial behavior: A developmental taxonomy. *Psychological Review*, 100(4), 674-701.
- ²Farrington, D. P. (1998). Predictors, causes, and correlates of male youth violence. In M. Tony & M. Moore (Eds.) *Youth and Violence: Vol 24. Crime and justice* 421-475. Chicago: University of Chicago Press.
- ³Rafferty, Y., & Shinn, M. (1991). The impact of homelessness on children. *American Psychologist*, 46(11), 1170-1179.
- ⁴Hadfield, J. (2010). MCMC methods for multi-response generalized linear mixed models: The MCMCglmm R package. *Journal of Statistical Software*, 33(2), 1 - 22.

This work was partially supported by the Interdisciplinary Education Sciences Training Program (IES Award # R305C050059; University of Minnesota PRF# 473473). We are indebted to Dr. Jarrod Hadfield, at the University of Edinburgh, for his statistical advice.