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

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Introduction/Background

- Delinquency emerges in the lower grades, peaks in middle and high school, and declines in adulthood[1]
- 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 adversity[3]
  - 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 should a reseacher deal with over dispersed longitudinal data where the majority of the students have no suspensions?

Research Questions

- Do suspensions follow a similar growth trajectory to other delinquent behaviors and is there a risk gradient?
- Is there a developmental component to suspensions? Do the timing and patterns of trajectories differ by gender or gender + ethnicity?
- Do models that account for zero-inflation fit better than traditional Poisson models?

Methods

Sample

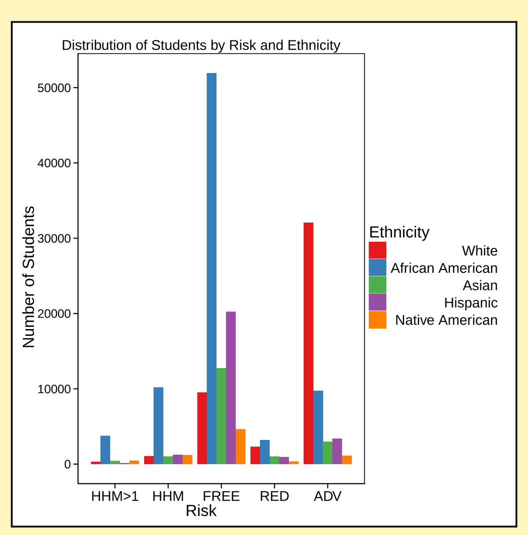
- Data were collected by Minneapolis Public Schools
  - 81,724 students in grades 1 - 12
  - 175,975 data points
  - All students included in study had complete data on the independent variables

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

Descriptive Stats

- 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 30,000 iterations to converge
    - Estimates parameters for binomial (zero-inflated) and Poisson components
    - Requires specification of a prior on B-, G-, and R- structures
    - However, the R-structure is fixed because the residual cannot be estimated in binomial models, but the G-structure is 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 schools)
  - Flat prior on B-structure ($\mu = 0$; $\sigma^2 =$I·1e10)
  - Prior on R-structure was fixed
  - G-structure had a half-Cauchy prior (scale parameter = 2)
- Compared growth curve to other delinquent behaviors and examined Bayesian confidence intervals and posterior modes

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 African American females should be first, followed by other groups

Analysis: Question 3

- Examination of proportion of students with no suspensions accounted for by:
  - Poisson component
  - Poisson + zero-inflation component

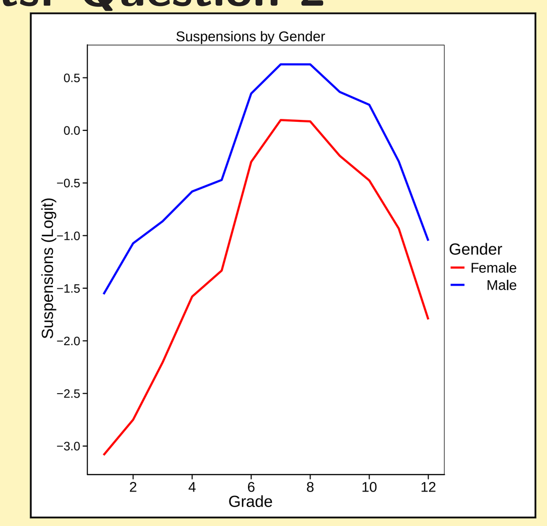
Results

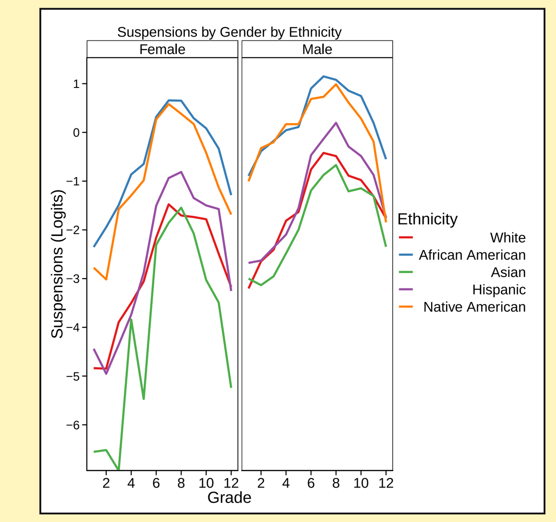
Results: Question 1

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

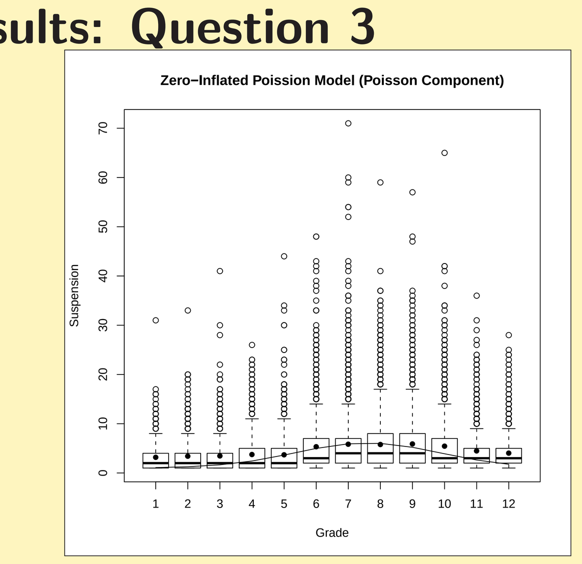
Results

Results: Question 2





Results: Question 3



Grade	Observed	Poisson	Poisson + Zero-inflation
1	0.96	0.83	0.91
2	0.94	0.62	0.80
3	0.92	0.33	0.66
4	0.90	0.12	0.55
5	0.88	0.03	0.50
6	0.80	0.01	0.49
7	0.74	0.00	0.49
8	0.74	0.00	0.49
9	0.81	0.01	0.49
10	0.82	0.02	0.50
11	0.87	0.10	0.53
12	0.94	0.28	0.63

Observed and Expected Proportion of Students Having No Suspensions by Grade

Conclusions

- Suspensions showed a similar growth trajectory to other delinquent behaviors
  - However, the timing was earlier (peaked in 7th and 8th grade)
- Strong school effect (not presented)
  - Should control for school-level effects when examining delinquency
- No difference in timing of crescendo by gender or gender + ethnicity
  - However, African American and non-Hispanic White students peaked earliest
- The zero-inflation component greatly increased the predictive validity
  - However, this is still does not account for all students with no suspensions
- The use of the zero-inflation Poisson models required the use of Bayesian statistics and MCMC
  - Bayesian approaches possess many optimality properties and allow development and testing of more complex models
  - A sensitivity analysis can be performed to examine robustness of posterior under different priors
- Future work will examine the ZIP and Poisson models with over dispersed data

References/Acknowledgments

[1]Moffitt, T. (1993). Adolescence-limited and life-course-persistent antisocial behavior: A developmental taxonomy.*Psychological Review*, 100(4), 674-701. [2]Farrington, 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. [3]Rafferty, Y., & Shinn, M. (1991). The impact of homelessness on children.*American Psychologist*, 46 (11), 1170-1179. [4]Hadfield, J. (2010). MCMC methods for multi-response generalized linear mixed models: The MCMCglmm R package. *Journal of Statistical Software*, 33(2), 1 - 22. We are indebted to Dr. Jarrod Hadfield, at the University of Edinburgh, for his statistical advice. **This work was supported by the Interdisciplinary Education Sciences Training Program (IES Award # R305C050059; University of Minnesota PRF# 473473).**