Strategies for Comparative Growth Modeling of Achievement in Homeless/Highly Mobile Students

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Introduction

Disparities in achievement have been shown to be associated with differences in risk.[1]

Students at higher risk are more likely to suffer developmental delays[2], have poorer health, and more behavioral problems.[3]

Homeless/highly mobile students (HHM) face even greater risk.[3]

There has been an increased federal focus on higher risk students with NCLB, but there is still a dearth in longitudinal studies.

Additionally, how should risk be treated: Episodic (dynamic) or chronic (static)?

Research Problem

This study aims to examine the predictive validity of treating risk as a static categorical or dynamic predictor of reading and math achievement and growth.

Methods

39,622 data points were collected on 16,561 students (grades 3 – 8) in a large, urban, Midwestern school district from 2004-2005 through 2007-2008.

Risk was defined as HHM, on free or reduced-price lunch but not HHM (POV), or as neither HHM nor POV (ADV). There were 1753 HHM, 10613 POV, and 4195 ADV students.

Other covariates examined include ethnicity, gender, special education status, English language learner (ELL), and average yearly attendance.

Two models were constructed: Static and Dynamic
- Static: All covariates were treated as static.
- Dynamic: Risk, special education, ELL, and attendance were treated as dynamic.

Quadratic mixed models[4] with all covariate slope and intercept interactions with random intercept only were initially fit to the data.

Model Selection Process
Step 1: Completely drop covariate and see if reduced model has better fit than full model with BIC[5]. Similar to an omnibus null hypothesis.
Step 2: Drop remaining covariate slope interactions and see if reduced model has better fit with BIC. Similar to slope null hypothesis.
Step 3: Add additional random effect and chose best model with BIC.

Table 1: Backwards elimination process used to select best model.

Results

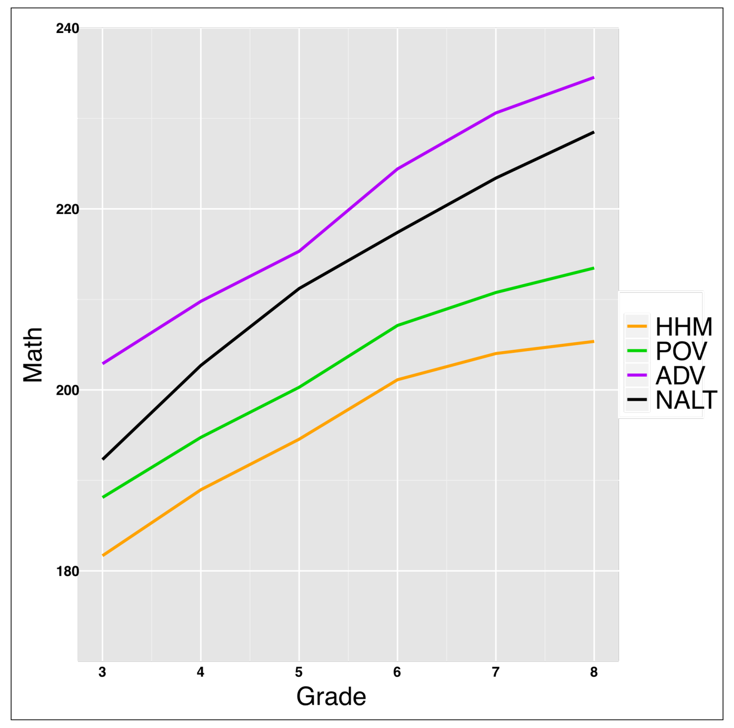

Figure 1: Connected means plot of math score by risk group.

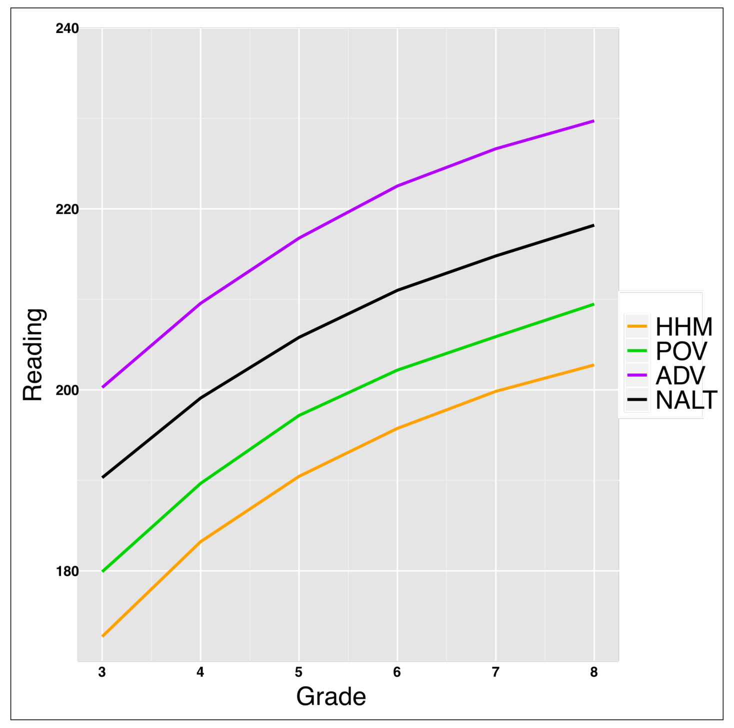

Figure 2: Connected means plot of reading score by risk group.

Model	Math	Reading
Static	210181.3	218883.1
Dynamic	212217.4	221195.0
$\Delta BIC = BIC_{STATIC} - BIC_{DYNAMIC}$	- 2036.1	- 2311.9

Table 2: BIC comparison of the selected static versus dynamic model for math and reading. A negative ΔBIC less than 2 favors the static model and a positive ΔBIC greater than 2 favors the dynamic model.

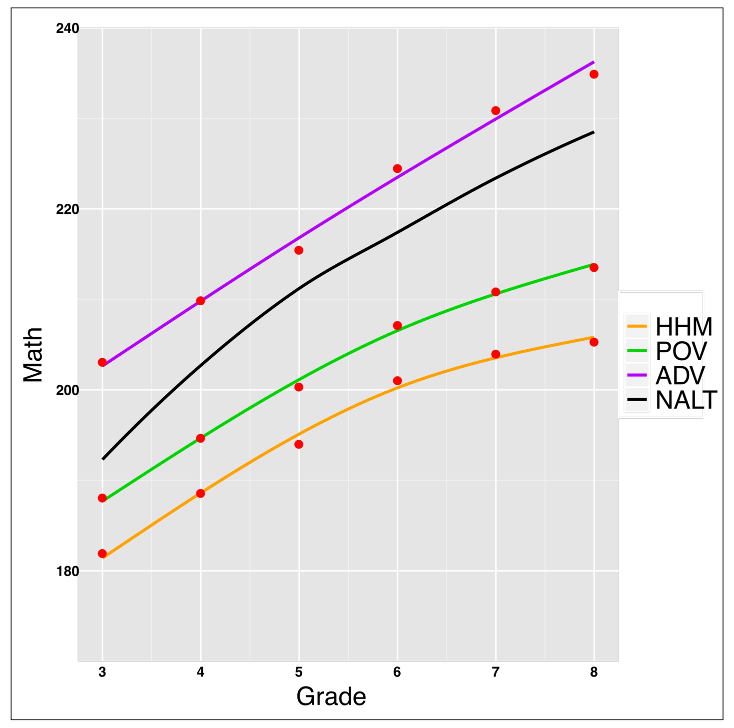

Figure 3: Smoothed curve of chosen model of math score by risk. Red circles indicate raw means.

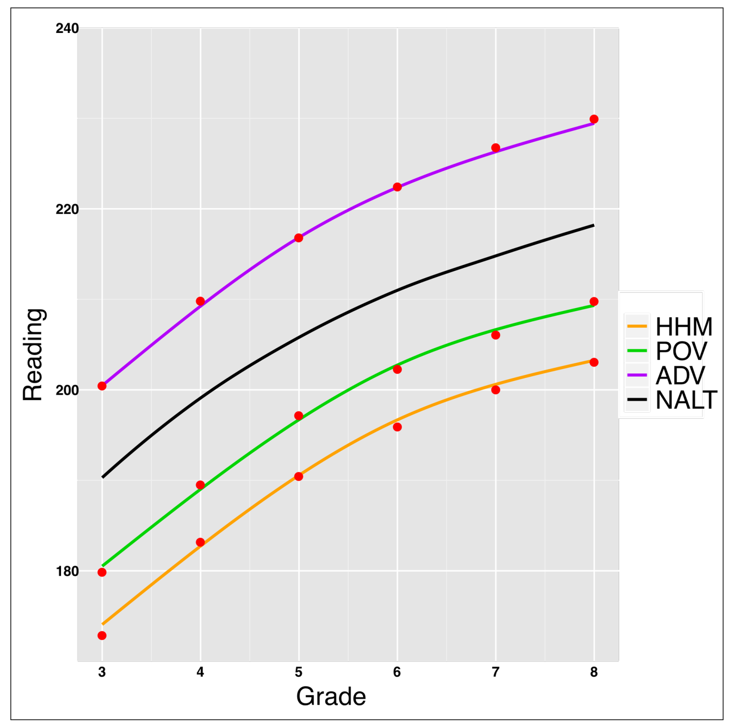

Figure 4: Smoothed curve of chosen model of reading score by risk. Red circles indicate raw means.

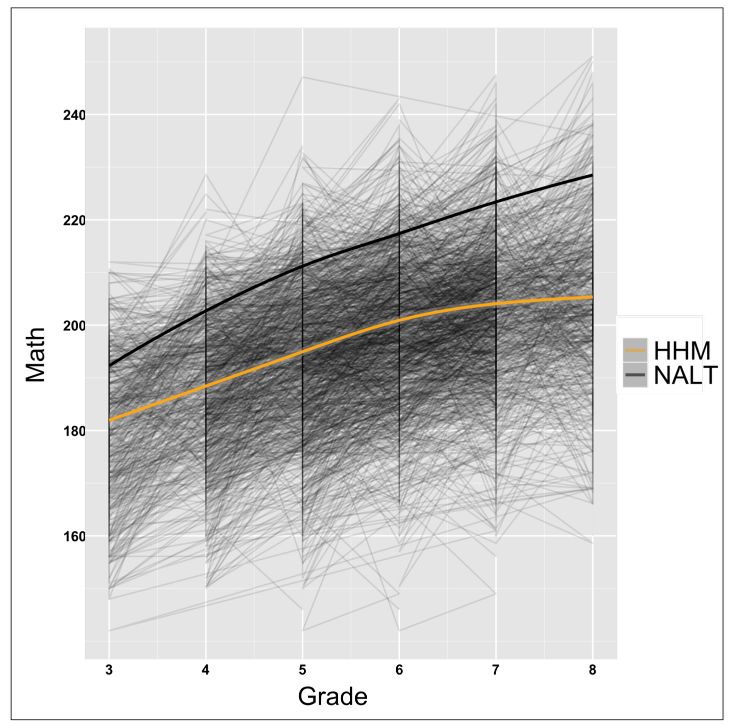

Figure 5: Individual math growth curves for HHM students.

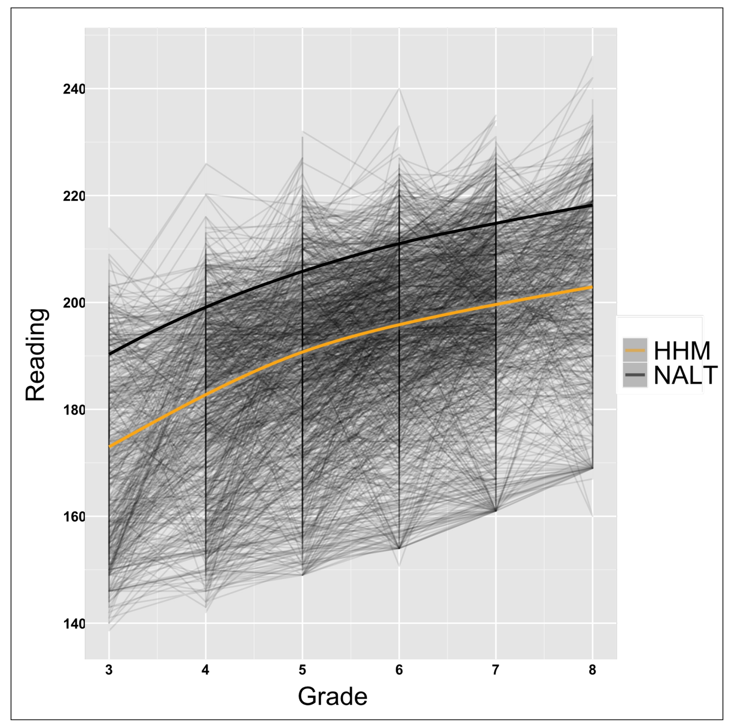

Figure 6: Individual reading growth curves for HHM students.

Parameter	Estimate (SE)	t-value
Intercept	160.18 (3.13)	51.13
POV	6.55 (1.76)	3.72
ADV	14.68 (1.90)	7.71
Special Ed	-10.93 (1.24)	-8.81
African American	-9.29 (0.39)	-23.84
Asian	-0.62 (0.57)	-1.09
Hispanic	-3.91 (0.53)	-7.41
Native American	-8.13 (0.69)	-11.87
Attendance	20.79 (2.82)	7.38
ELL	-8.24 (0.42)	-19.76
Grade	8.44 (0.62)	13.56
$Grade^2$	-0.53 (0.05)	-9.75
POV*Grade	-0.78 (0.65)	-1.20
ADV*Grade	-1.31 (0.69)	-1.90
Special Ed*Grade	0.41 (0.46)	0.89
$POV*Grade^2$	0.07 (0.06)	1.32
$ADV*Grade^2$	0.17 (0.06)	2.72
Special $Ed*Grade^2$	-0.08 (0.04)	-2.04

Parameter	Estimate (SE)	t-value
Intercept	133.46 (2.40)	55.64
POV	5.02 (0.40)	12.58
ADV	14.68 (0.51)	28.92
Special Ed	-15.58 (0.31)	-51.03
African American	-9.47 (0.36)	-26.67
Asian	-3.93 (0.51)	-7.65
Hispanic	-4.95 (0.48)	-10.28
Native American	-7.46 (0.63)	-11.84
Attendance	21.99 (2.47)	8.89
ELL	-16.20 (1.27)	-12.78
Grade	13.91 (0.23)	59.68
$Grade^2$	-0.75 (0.02)	-35.67
ELL*Grade	0.96 (0.45)	2.14
$ELL*Grade^2$	-0.01 (0.04)	-0.37

Table 3 (left) and Table 4 (above) show the parameters, parameter estimates, standard errors, and t-values for the best fitting math and reading models. Both models were static models.

Discussion

Results suggest that risk is not episodic and is best modeled as a static covariate.

- However, risk may be dynamic but requires greater than 4 years for recovery or less "noisy" data.

Risk is an important predictor for math and reading achievement with risk by grade interactions present in math achievement.

There is high variation and resilience in the HHM group.

Future work involves developing interventions targeting both high risk students and their parents.

References

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Acknowledgements

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