Methods for Finding for Whom an Intervention is Effective and under what Circumstance

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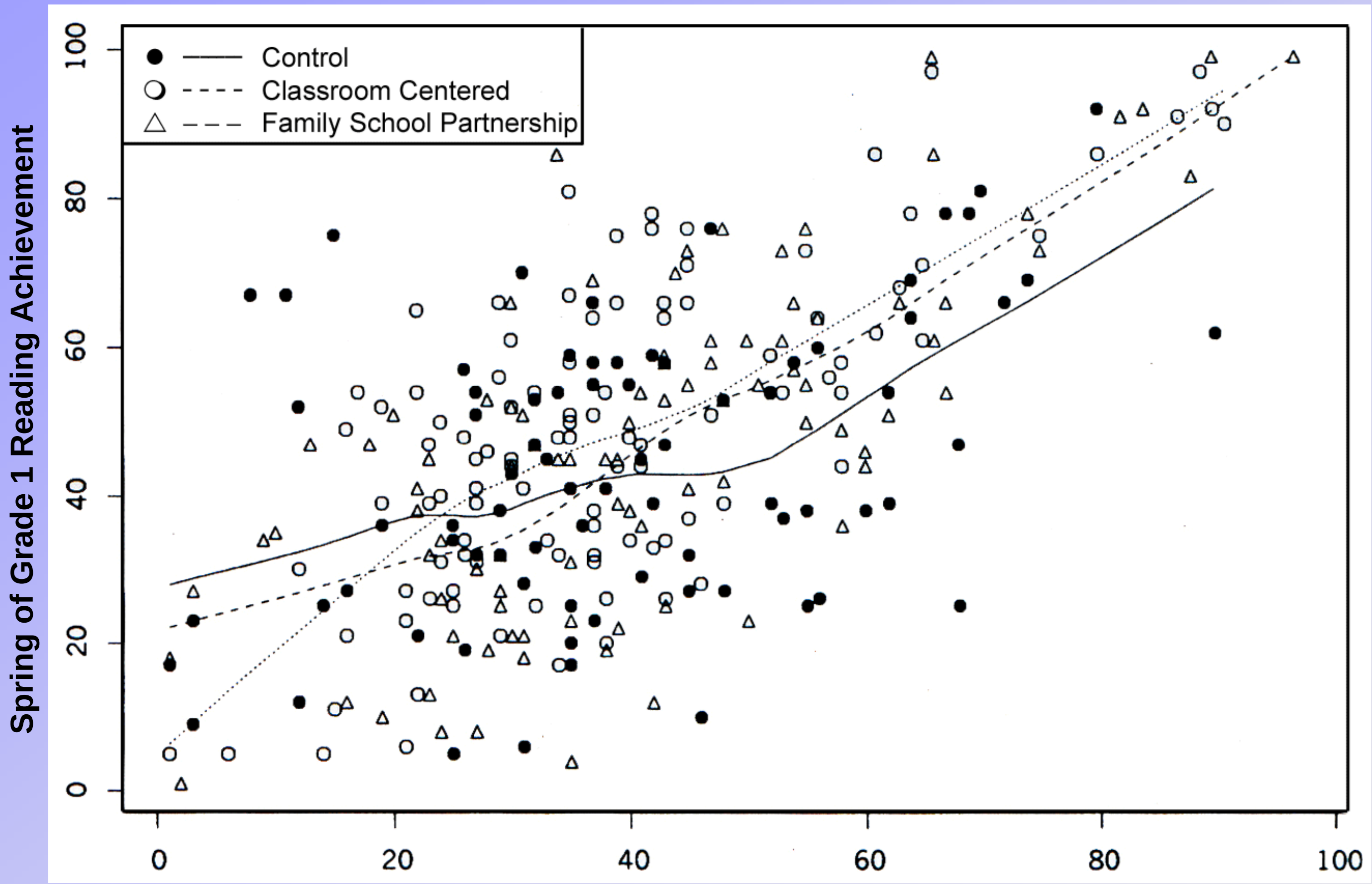
Overview

- Intervention effects: variation in impact, interactions
- Longitudinal data: more than two time points
- Hierarchical data: individuals within groups

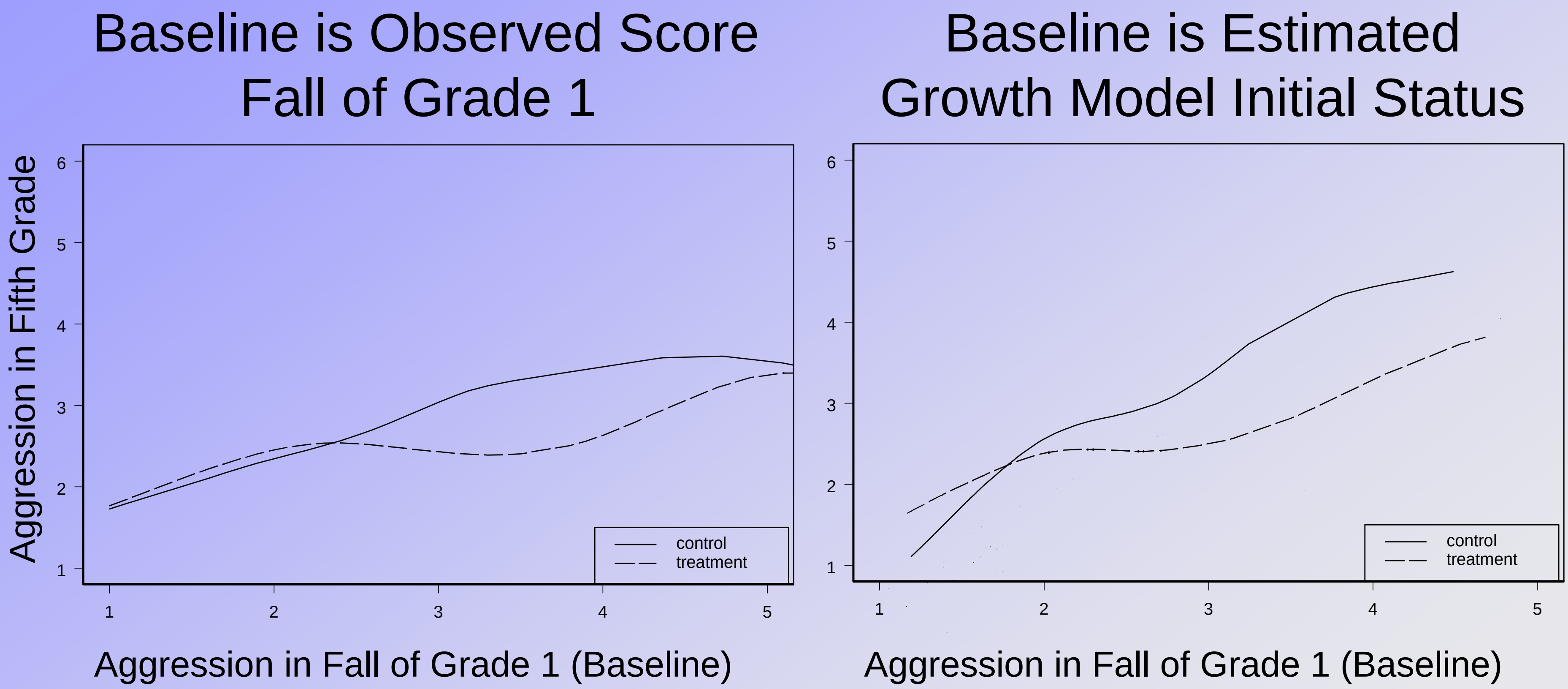
Example 1: Baltimore reading treatment-baseline interaction



Fall of Grade 1 Reading Achievement (Normal Curve Equivalent)

*Source: Ialongo LN, Werthamer S, Kellam SK, Brown CH, Wang S, Lin Y (1999). Proximal Impact of Two First Grade Preventive Interventions on the Early Risk Behaviors for Later Substance Abuse, Depression and Antisocial Behavior. American Journal of Community Psychology, 27, Vol, 5, 599-641.

Example 1B: Baltimore aggression treatment-baseline interaction

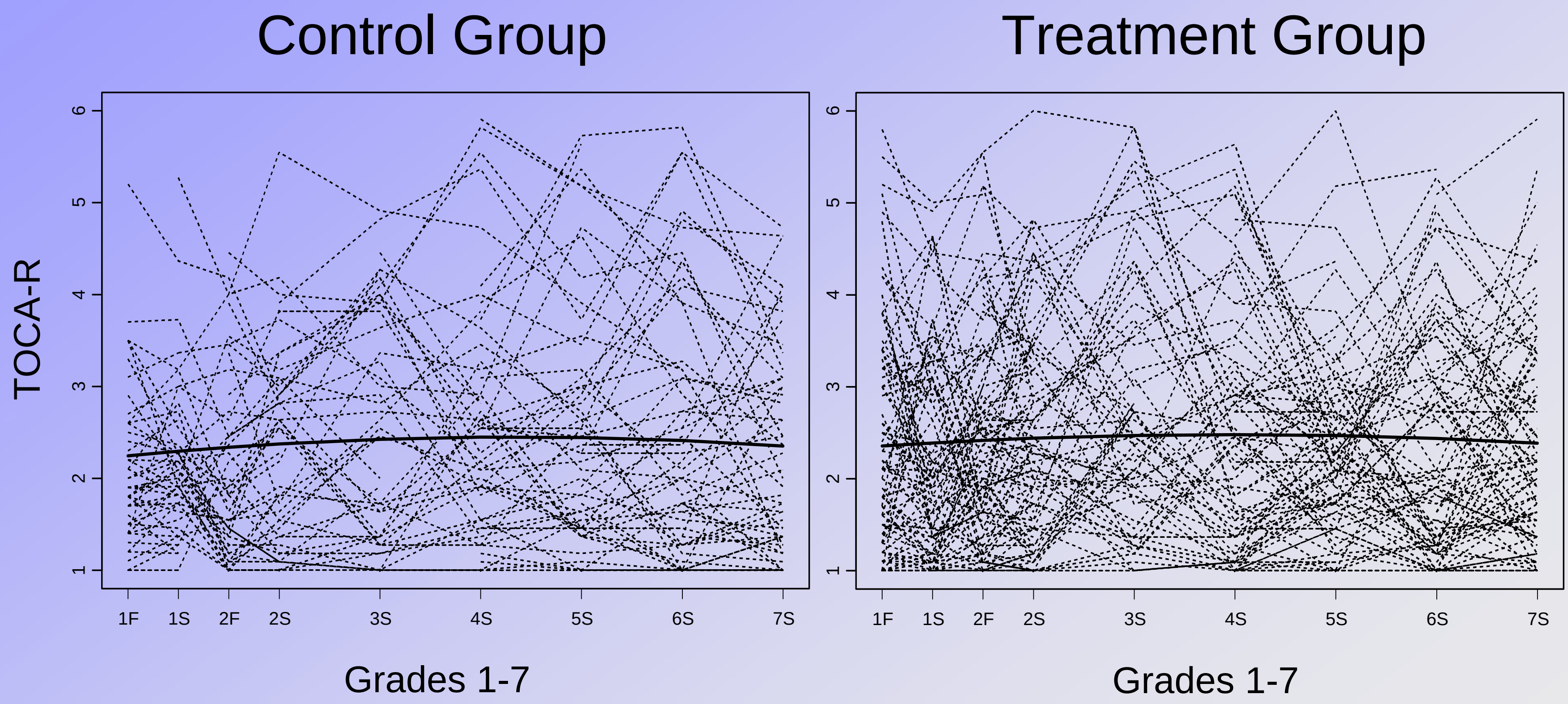


*Source: Khoo, S.T. (2001). Assessing program effects in the presence of treatment-baseline interactions: A latent curve approach. Psychological Methods, 6, 234-257.

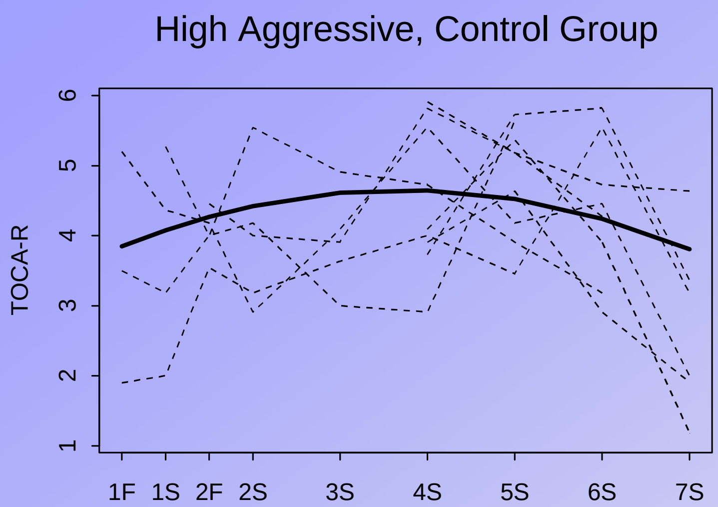
Weaknesses of pretest-posttest analysis (GAM – Generalized Additive Modeling ANCOVA – Analysis of Covariance)

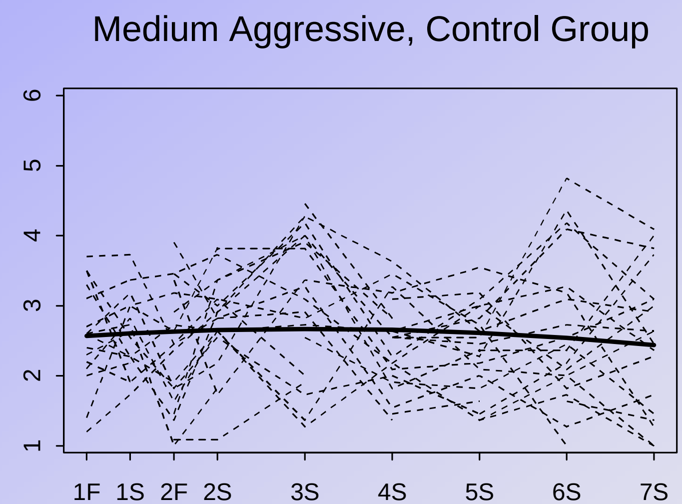
- Posttest at a single time point does not show the initiation and duration of impact
- Pretest is a fallible baseline measure due to time-specific variation and measurement error
  - Avoid weaknesses by collecting longitudinal data (more than 2 time points) and using growth modeling

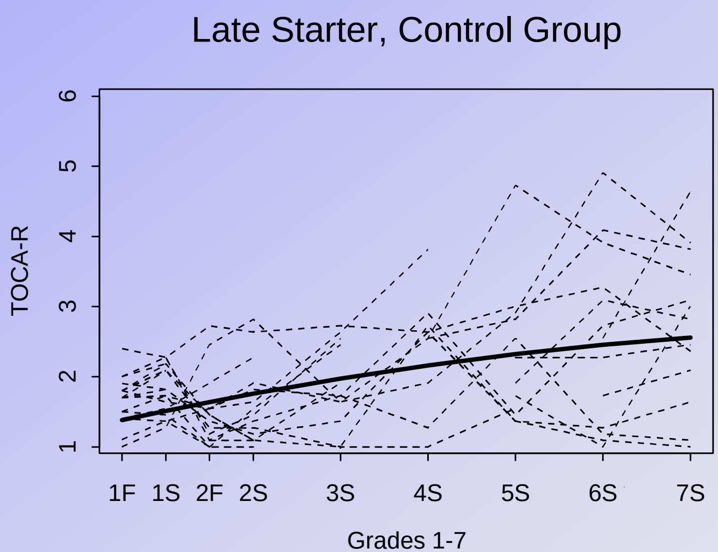
Example 1B: Aggression development control and treatment groups

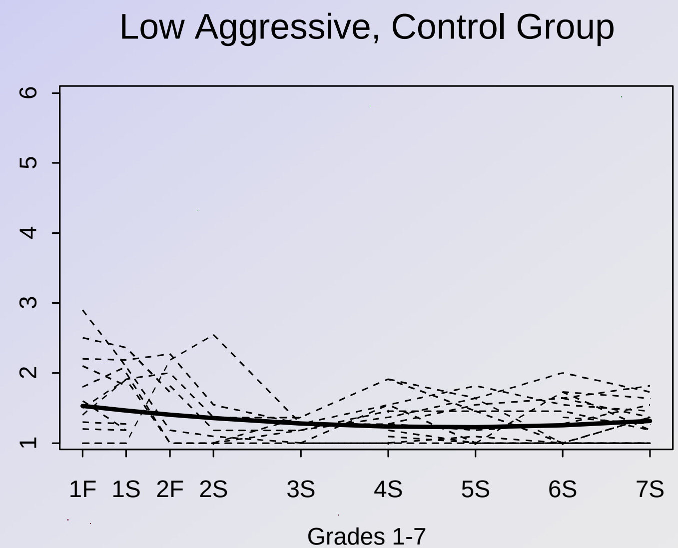


Example 1B: Aggression development control group sorted by trajectories

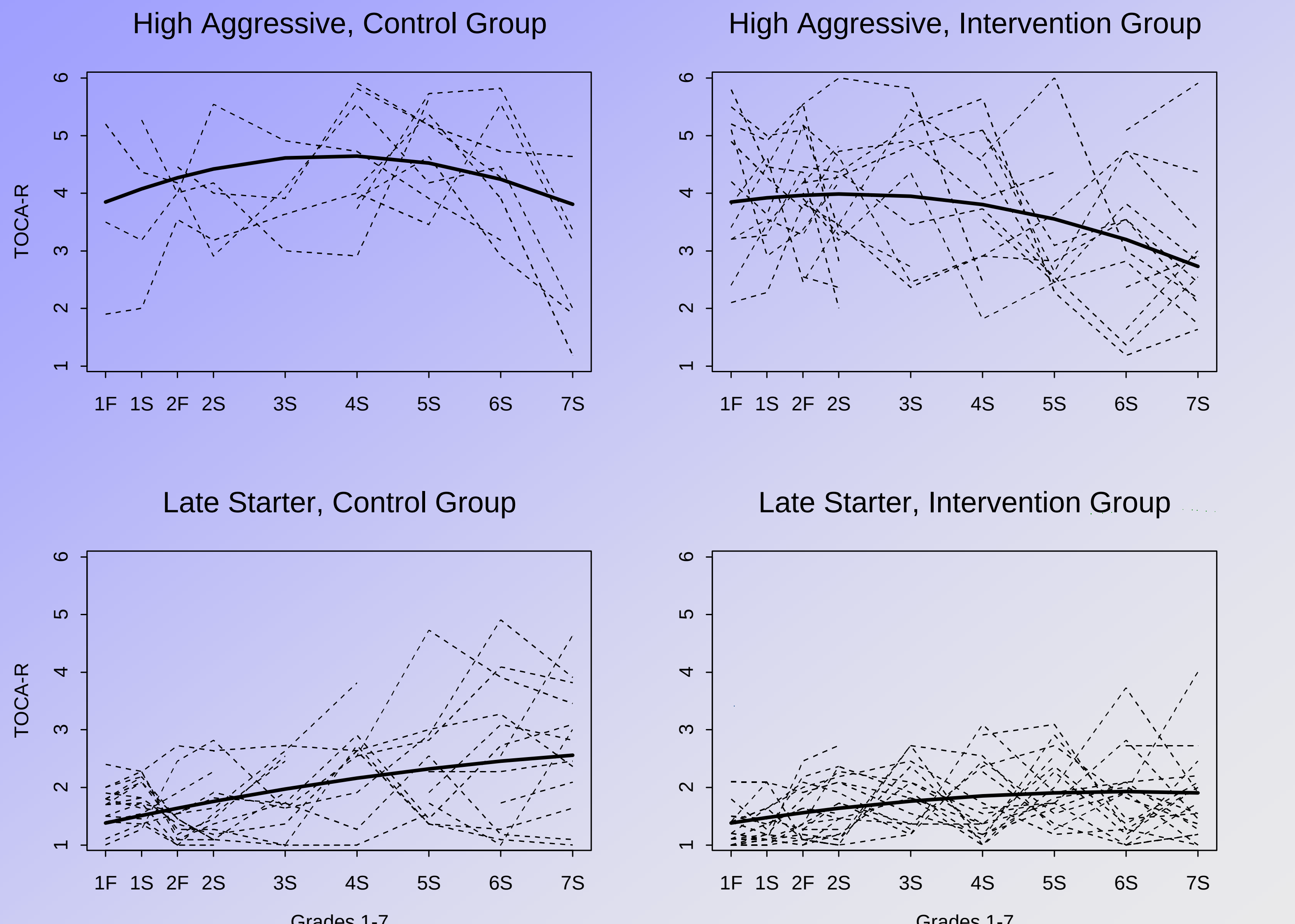








Example 1B: Aggression development trajectory classes for control and intervention groups



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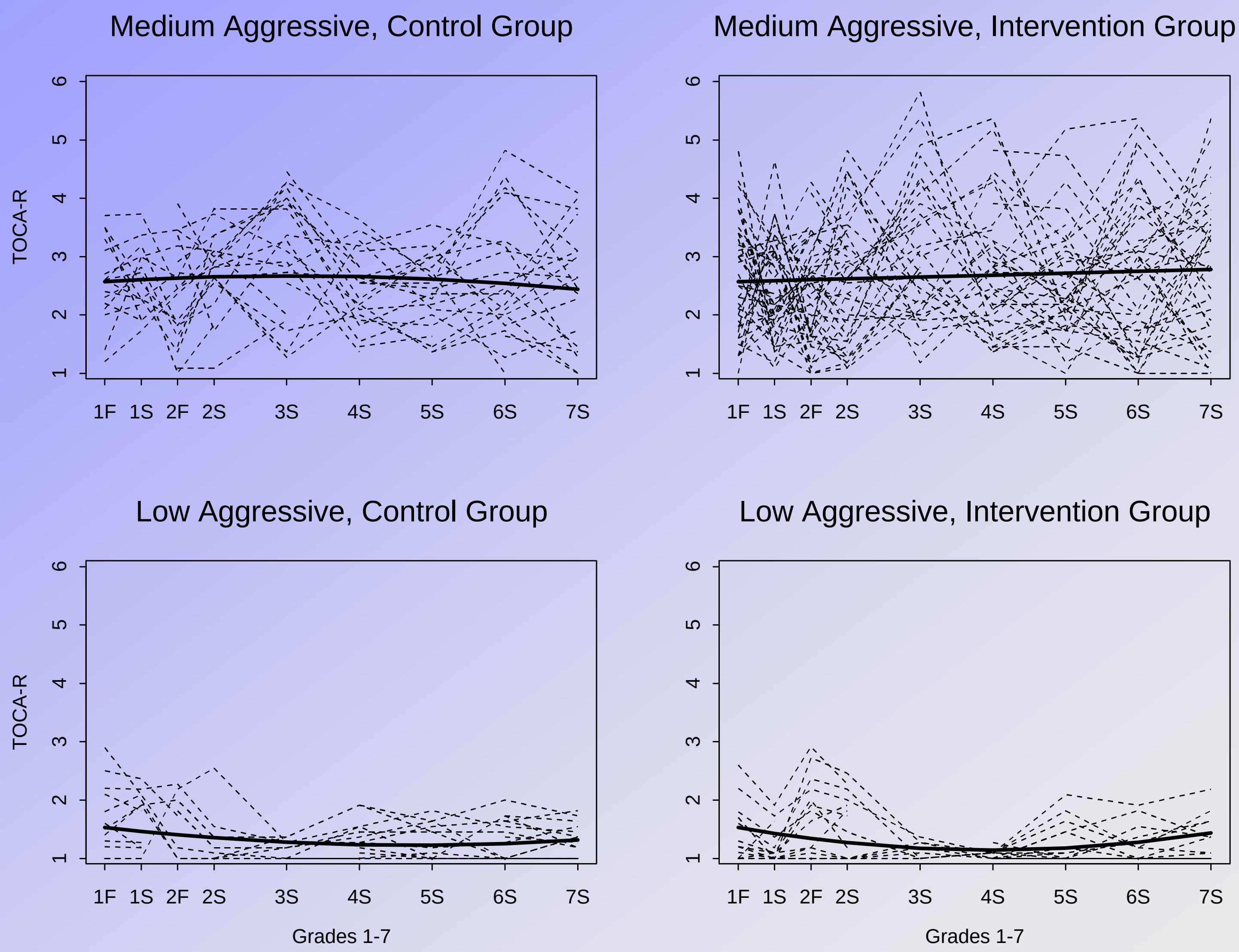

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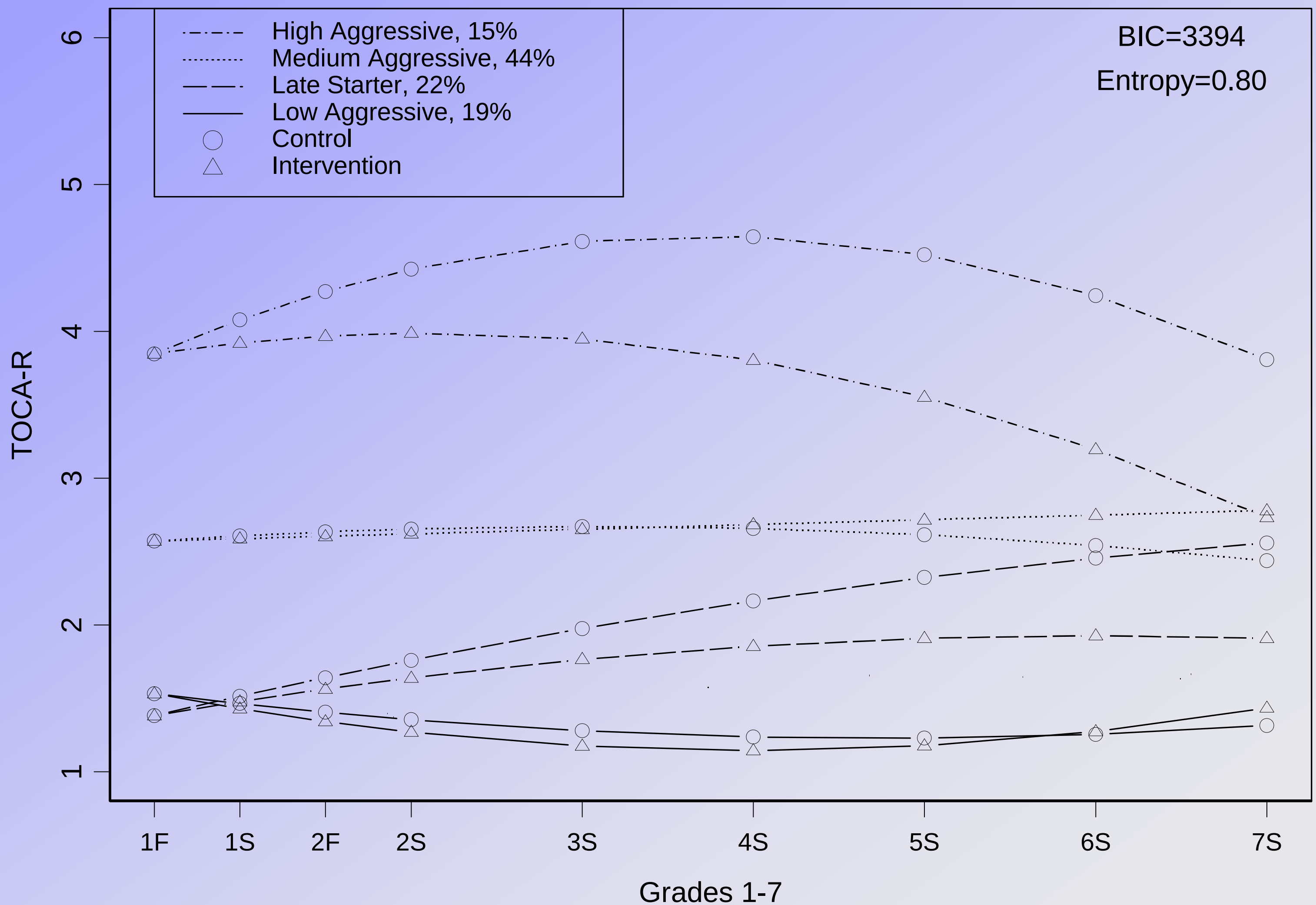

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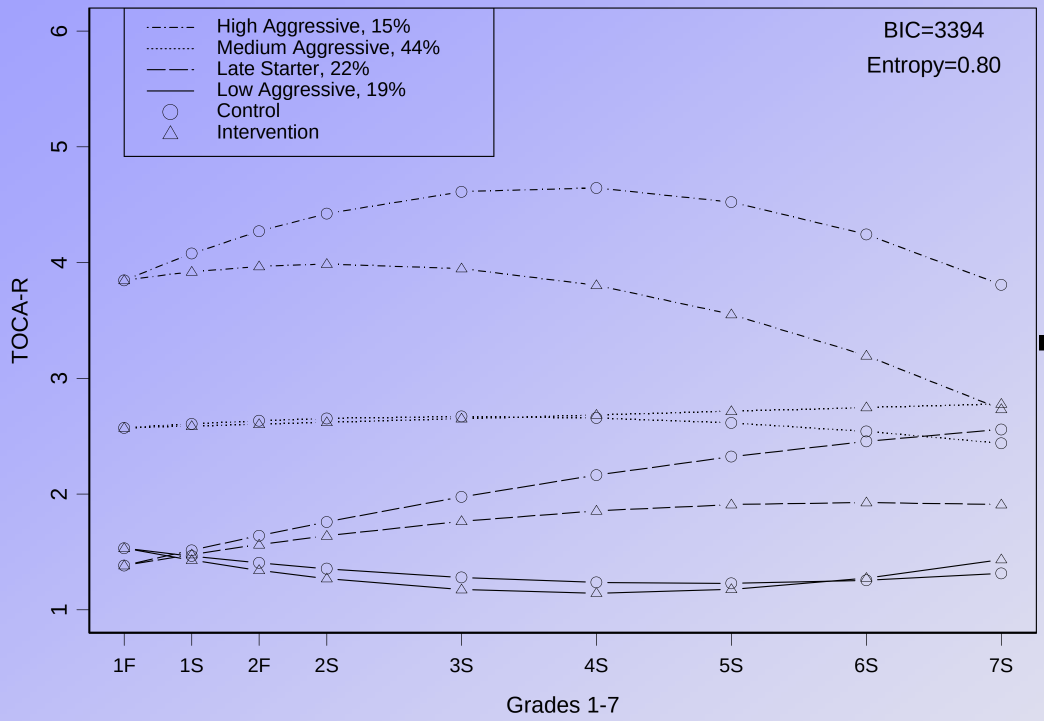
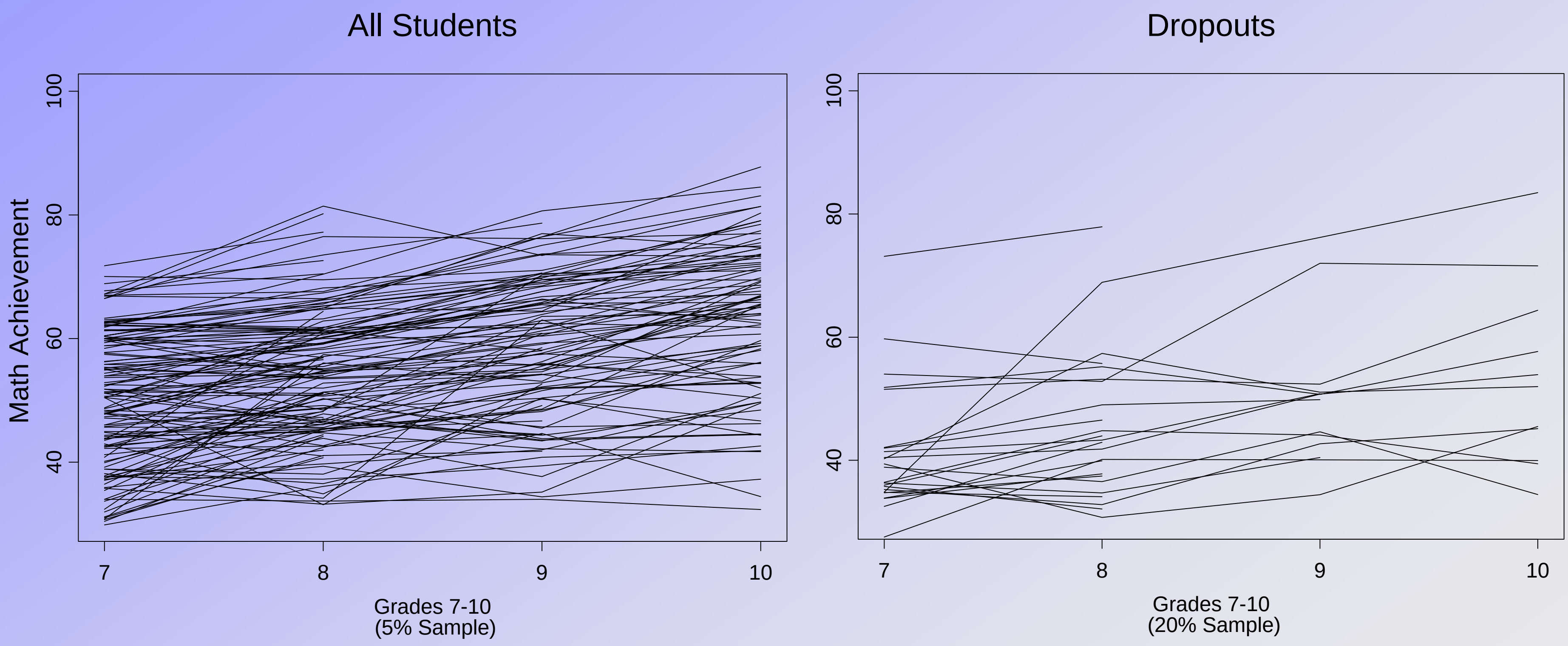


Juvenile Court Record

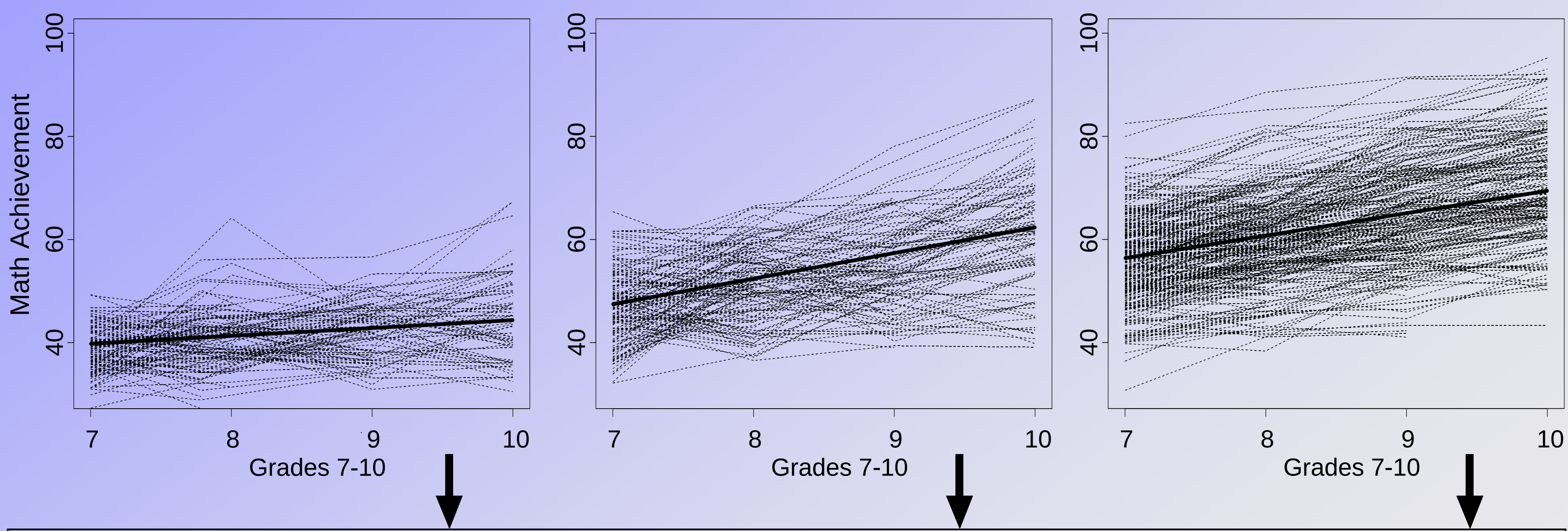
Class	Control	Intervntn
High	80%	52%
Medium	33%	40%
LS	49%	20%
Low	25%	10%

Example 2: LSAY math achievement in Seventh through Tenth Grade and high school dropout



Example 2: LSAY math achievement trajectory classes predicting high school dropout

Poor Development: 20% Moderate Development: 28% Good Development: 52%



Dropout:	69%	8%	1%

Example 3: The New York School Choice Study*

◆ Setting:	Lottery for 20,000 applicants from low-income families attending First through Fifth Grade in NY public schools
◆ Treatment:	$1,400 dollar annual scholarships for 3 years in private schools
◆ Sample:	1,960 families (controls and treatment; balanced)
◆ Design:	Propensity matched pairs design and randomized block
◆ Design variable:	low/high applicant school (test scores below/above city-wide median)
◆ Measures:	Spring 1987 pretest, Spring 1988 posttest; reading and math (ITBS)

*Source: Barnard, J., Frangakis, C.E., Hill, J., Rubin, D.B. (in press). A principal stratification approach to broken randomized experiments: A case study of school choice vouchers in New York City. Forthcoming in J. of the Am. Stat. Assoc.

Example 3 Continued: The New York School Choice Study

Results

- Effect of private school attendance (CACE): 5 percentile points for math in low schools
- Effect of winning the lottery (ITT): 3 percentile points for math in low schools

Complications

- Adherence classes: 20-25% of those who won declined scholarship, 6-10% of those who did not win sent their children to private schools nevertheless
- Missing data: on covariates and on posttest as a function of adherence classes

New analytical tools

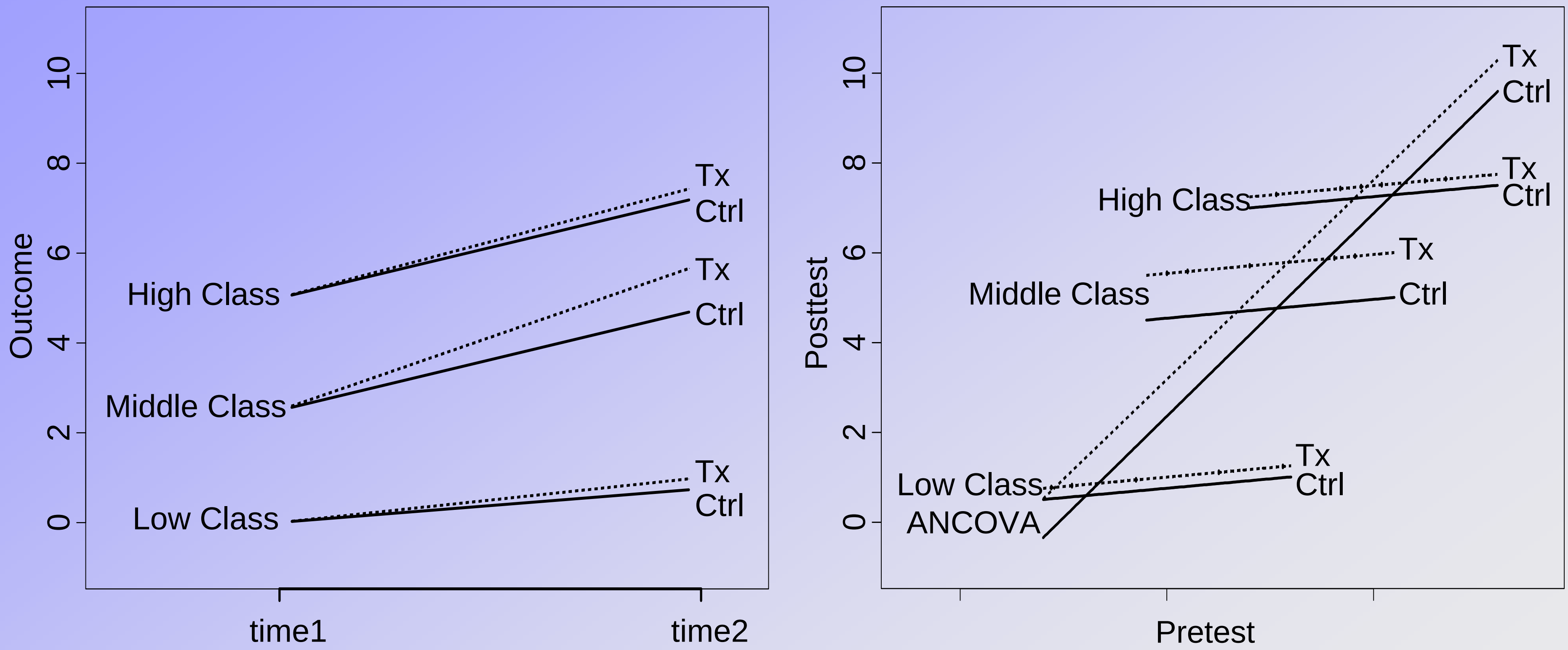
- Growth mixture modeling – see Slides 165, 166
- Multilevel modeling – see Slides 167, 168
- Missing data modeling – see Slide 169
- Adherence class modeling – see Slide 170
- Structural equation modeling – see Slide 171
- Software and Literature – see Slide 172

Growth and growth mixture modeling

- Captures intervention impact on trajectories in an efficient and flexible way

- Captures intervention effects that vary across individuals

Weaknesses of pretest-posttest ANCOVA as compared to growth mixture modeling



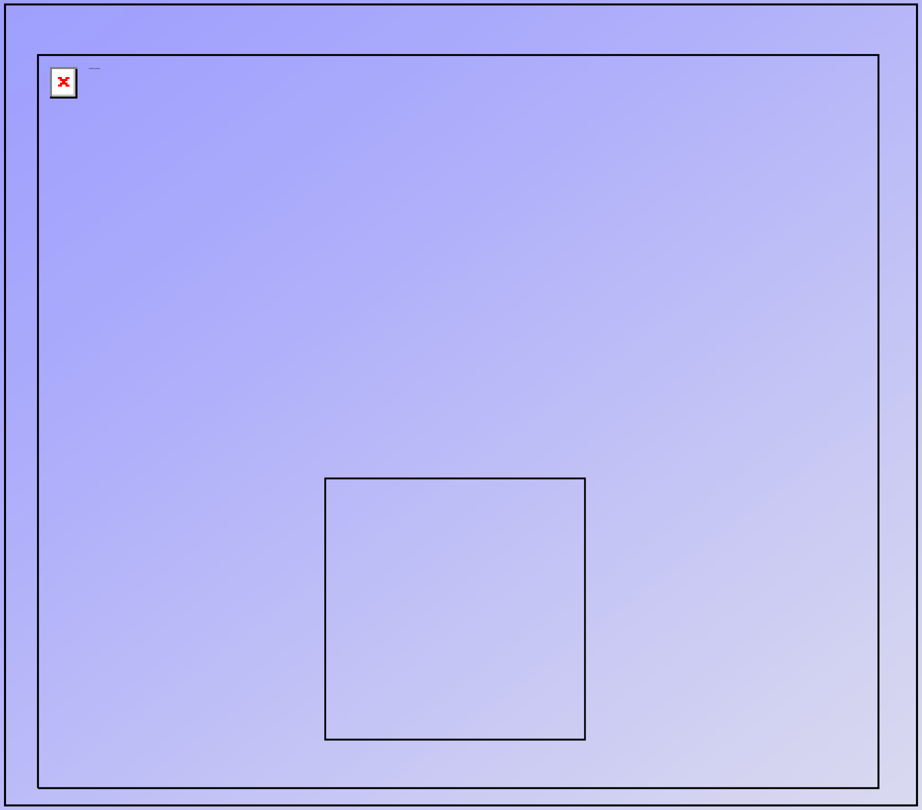
Multilevel modeling

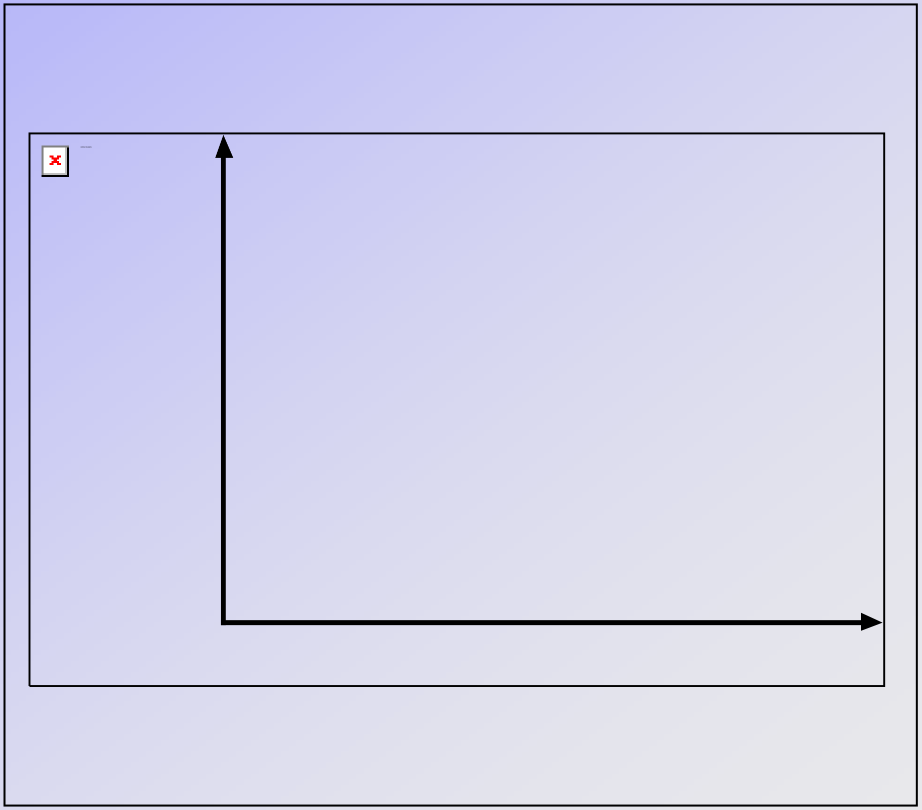
- Children in different classrooms (different teachers) and schools may benefit differently from an intervention (Aggression, LSAY, New York examples)

- Individual-level relationships can vary across classrooms/schools

- Variation can be explained by classroom- and school-level variables

Cross-level interactions





Missing data modeling

- Attrition in longitudinal studies
- Designed selection of children into treatment: cross-sectional and longitudinal screens

Latent adherence class modeling (CACE Analysis)

- Adherers and non-adherers are often quite different
- Latent class modeling where adherence is observed in intervention group and unobserved in control group

Structural equation modeling latent variable modeling

- Mediational modeling – for example, “path analysis” in a pretest-posttest design where intervention effect on outcome is mediated by implementation

- General latent variable modeling – for example, longitudinal analysis where class size influences achievement development, which influences high school dropout (Tennessee STAR study)

Software and literature

- Multilevel modeling including growth modeling (with missing data): GLLAMM, HLM, MIXOR, MLwiN, Mplus, SAS PROC MIXED
- Growth mixture modeling: Mplus, SAS PROC TRAJ
- Latent (adherence) class (CACE) modeling: Mplus
- Structural equation modeling: Amos, EQS, LISREL, Mplus, Mx
- Latent variable modeling: Mplus
  - Mplus-related references can be downloaded from www.statmodel.com (see home page, References, Randomized Trials)
    - Overview in Muthén (2002) Behaviormetrika

Key Points

- Collect rich pre-intervention information to enable thorough investigation of treatment-baseline interactions

- Collect longitudinal data at more than one post-intervention time point to enable investigation of intervention impact on trajectories

- Use growth mixture modeling and multilevel modeling to find variation in impact