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Title: Exploring the Aptitude-by-Treatment Interaction for Latent Subgroups

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Background/Context:

Individual students differ in their response to an intervention with some showing the intended effect and others showing little or none. Intervention researchers with interest in learning disabilities have thus explored how educators can provide the inadequately responsive children with differentiated and effective instruction. In special education literature, this idea has often been described by the term *aptitude-by-treatment interaction*, or ATI (Fuchs et al., 2014).

One common approach to explore such ATI is to specify, test, and communicate interaction or moderation effects usually within a linear regression model (Preacher & Sterba, 2019). Most study authors focus on one or two moderators contrasting treatment effects of subgroups defined solely by the level of the individual moderator (e.g., Fuchs et al., 2014). However, many learning disabilities are characterized by multiple potential predictors, most of which might have small moderation effects individually. Thus, it is crucial to consider the *joint effect modification* of multiple observed student characteristics. But when the number of the potential moderators is moderate to large, linear regression models become unstable and difficult to interpret.

Purpose:

In this study, we apply a dimension reduction method, the latent profile analysis (LPA), to assess the joint effect modification of multiple potential moderators. Children may respond to treatment differently depending on some latent risk profile such as overall academic deficit severity. We aim to identify a few clinically meaningful latent risk subgroups that are determined by multiple observed covariates, and then estimate the heterogeneity of treatment effect across the latent subgroups.

This study employs a two-stage estimation approach. At the first stage, we examine the latent profiles that best characterize the cognitive skills of at-risk learners across pre-treatment measures of reading comprehension, word reading, IQ, and working memory. At the second stage, we conduct Bayesian analyses of heterogenous treatment effects across the specified latent subgroups. We examine whether the reading intervention affected at-risk learners in the 4^{th} and 5^{th} grades uniformly or differently such that one latent subgroup of sample benefited more than another.

Research Design/Intervention/Data Collection:

This study analyzes data collected from a cohort of a federally funded efficacy project, the Accelerating the Academic Achievement of Students with Learning Disabilities Research Initiative (A3 Initiative). The purpose of the A3 Initiative is to develop and evaluate the efficacy of math and reading interventions for students with learning disabilities in grades 3–5. In the A3 reading project, Tier 2 reading intervention is conducted by tutors for 15 weeks, three times per week, 45 minutes per session with students in grades 3-5 who have reading difficulties. We use the A3 reading project data collected in 2017-2018 academic year (Year 5). The final analytic sample contains 67 teachers of the 189 children (87 4^{th} graders and 102 5^{th} graders). The 189 children were randomly assigned to the control group ($n = 64$) and two treatment groups ($n = 125$). We calculated factor scores to index Reading Comprehension, Transfer, Word Reading, Working Memory, and IQ at pre- and post-treatment across measures (Figure 1).

Data Analysis:

At stage 1, we conduct the LPA. As a model-based method, LPA provides statistical tests and goodness of fit indices for testing hypotheses about the number of classes that exist in the population of interest. Assuming the ten pre-treatment measures follows multivariate normal distribution, we fitted a series of model assuming one to eleven number of subgroups and picked the model with best goodness of fit. An analytic hierarchy process (Akogul & Erisoglu, 2017) suggests the best solution is the four latent classes model assuming equal variances and zero covariances (Figure 2).

At stage 2, we first calculate the gain scores and estimate the subgroup-specific treatment effects on them. Here, subgroup is defined by the combination of four latent classes and two grades (4^{th} and 5^{th}). Then, we model the heterogeneity across the estimated subgroup-specific effects using the Bayesian shrinkage model with non-informative priors (Wang et al., 2019). This Bayesian approach allows precision of estimation with the small sample size and facilitates interpretation that can be more readily understood by researchers, practitioners, and other stakeholders (Henderson et al. 2016).

Findings/Results/Conclusions:

At stage 1, the four profiles of pre-treatment cognitive skills were found among at-risk 4^{th} and 5^{th} graders: (1) Readers with global strengths, (2) Readers with global weaknesses, (3) Average readers with high word reading skills, and (4) Average readers with low word reading skills (Figure 3). The profiles were basically ordinal in the severity of their weaknesses. The order of severity is relatively defined, however, since the students in the sample were all identified as at risk. Two profiles of average readers were distinguished by their levels of word reading skills, which is consistent with the previous findings from Brasseur et al. (2011).

At stage 2, we found that readers with global weaknesses (Class 2) benefit more from the intervention than those with global strengths (Class 1), particularly for the gains in reading comprehension measures (WIAT3, GATES, and Mid transfer. See Figure 4). These results indicate that the reading intervention particularly benefited the youngsters with relatively low pre-treatment cognitive skills, compensating learning more for low-aptitude learners (*compensatory interaction*, Preacher & Sterba, 2019).

We also found that average readers with low word reading skills (Class 4) benefit more from the intervention than those with high word reading skills (Class 3), only for the gains in word reading measure, TOWRE Sight Word Efficiency. The probability that the effect for 4th grade average readers with low word reading skills is larger than the effect for those with high word reading skills in the same grade was 91% (Figure 5). This is consistent with the previous finding (Fuchs et al., 2019) supporting compensatory moderation of pre-treatment word reading.

References

Akogul, S., & Erisoglu, M. (2017). An approach for determining the number of clusters in a model-based cluster analysis. *Entropy, 19*(9), 452.

Brasseur-Hock, I. F., Hock, M. F., Kieffer, M. J., Biancarosa, G., & Deshler, D. D. (2011). Adolescent struggling readers in urban schools: Results of a latent class analysis. *Learning and Individual Differences, 21*(4), 438-452.

Fuchs, L. S., Schumacher, R. F., Sterba, S. K., Long, J., Namkung, J., Malone, A., ... & Changas, P. (2014). Does working memory moderate the effects of fraction intervention? An aptitude–treatment interaction. *Journal of Educational Psychology, 106*(2), 499.

Henderson, N. C., Louis, T. A., Wang, C., & Varadhan, R. (2016). Bayesian analysis of heterogeneous treatment effects for patient-centered outcomes research. *Health Services and Outcomes Research Methodology, 16*(4), 213-233.

Preacher, K. J., & Sterba, S. K. (2019). Aptitude-by-Treatment Interactions in Research on Educational Interventions. *Exceptional Children, 85*(2), 248-264.

Wang, C., Louis, T. A., Henderson, N. C., Weiss, C. O., & Varadhan, R. (2018). beanz: An R Package for Bayesian Analysis of Heterogeneous Treatment Effects with a Graphical User Interface. *Journal of Statistical Software, 85*(1), 1-31.

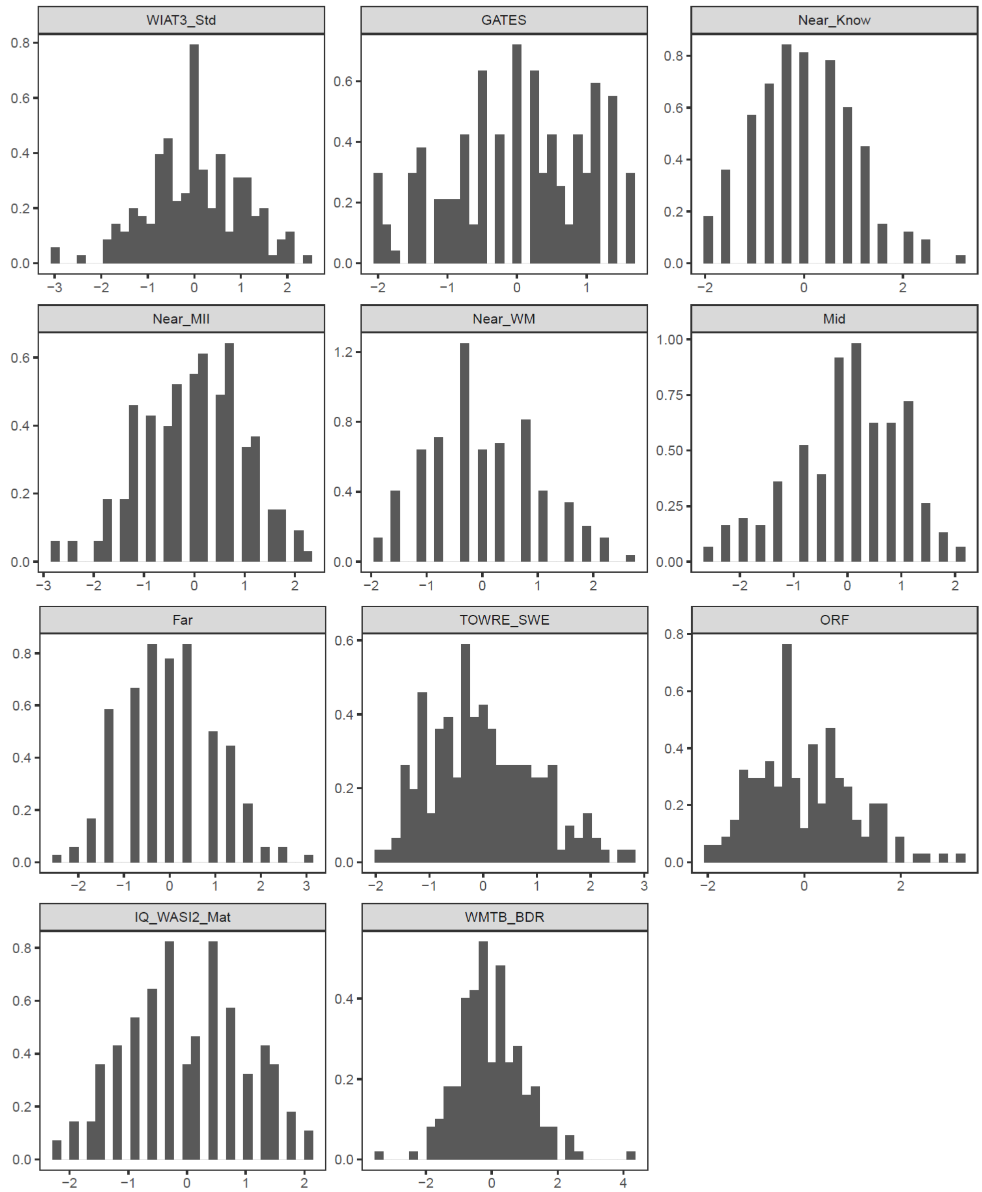


Figure 1. The distribution of each pre-treatment measure

Note: Each of the measure is a mean-centered and scaled factor score of the following test: (1) *WIAT3_std*: The subset of the Wechsler Individual Achievement Test-III (WIAT-3); (2) *GATES*: The Gates-MacHinitie Reading Tests-4; (3) *Near_Know*: Near-Transfer Knowledge Acquisition Test; (4) *Near_MII*: Near-Transfer Main Idea and Recall; (5) *Near_WM*: Near-Transfer Working Memory; (6) *Mid*: Mid-Transfer Test of Reading Comprehension; (7) *Far*: Far-Transfer Test of Reading Comprehension; (8) *TOWRE_SWE*: The Sight Word Efficiency subset of the Test of Word Reading Efficiency-2; (9) *ORF*: The Oral Reading Fluency subset of the Woodcock Reading Mastery Tests-3; (10) *IQ_WASI2_mat*: The Wechsler Abbreviated Scale of Intelligence 2 – Matrix Reasoning; (11) *WMTB_BDR*: The Backward Digit Recall subset of the Working Memory Test Battery for Children

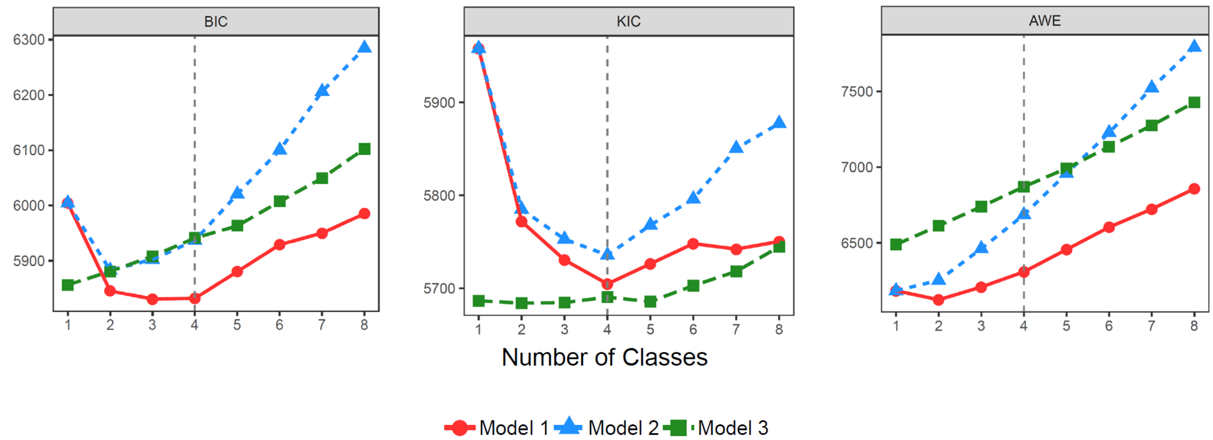


Figure 2. Change of the fit indices (BIC, KIC, and AWE) depending on model specification and the number of assumed latent subgroups

Note: Latent Profile Analysis model specification: (a) Model 1: equal variances and covariances fixed to zero; (b) Model 2: varying variances and covariances fixed to zero; (c) Model 3: equal variances and equal covariances. Since all pre-treatment measures are scaled (i.e., divided by their own standard deviations), we expect equal variances. Correlation matrix suggests that correlations vary but many fall within (-0.2, 0.2] range. Thus, we need to test multiple assumptions and pick by fits. An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is Model 1 with 4 classes.

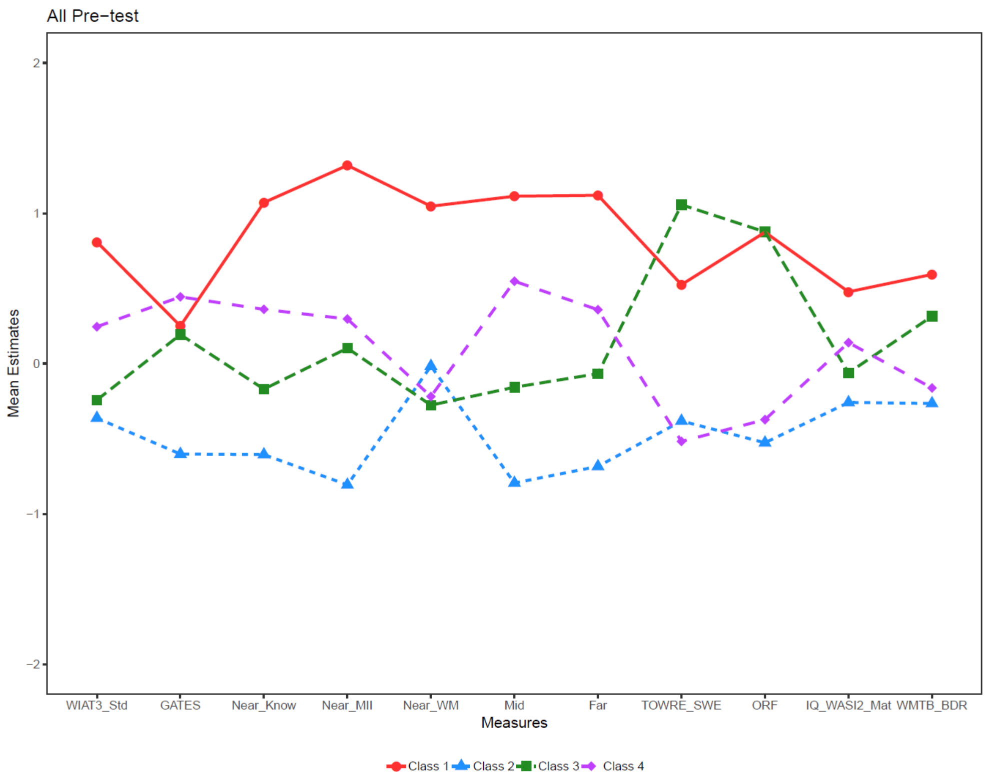


Figure 3. The four-profile solution of Latent Profile Analysis (LPA)

Note: (a) Class 1 Readers with global strengths: This class performed above all other classes in general on most of pre-treatment cognitive skills (N=23, 12% of sample); (b) Class 2 Readers with global weaknesses: This class performed below all other classes in general on most of pre-treatment cognitive skills (N=65, 34% of sample); (c) Class 3 Average readers with high word reading skills: This class demonstrated all other measures in the average range but word reading skills (TOWRE SWE, ORF) that were above average (1 SD above average) (N=39, 21% of sample); (d) Class 4 Average readers with low word reading skills: This class demonstrated all other measures in the average range but word reading skills (TOWRE SWE, ORF) that were below average (the same as class 2) (N=62, 33% of sample).

Class 1: Readers with global strengths

Class 2: Readers with global weaknesses

Class 3: Average readers with *high* word reading skills

Class 4: Average readers with *low* word reading skills

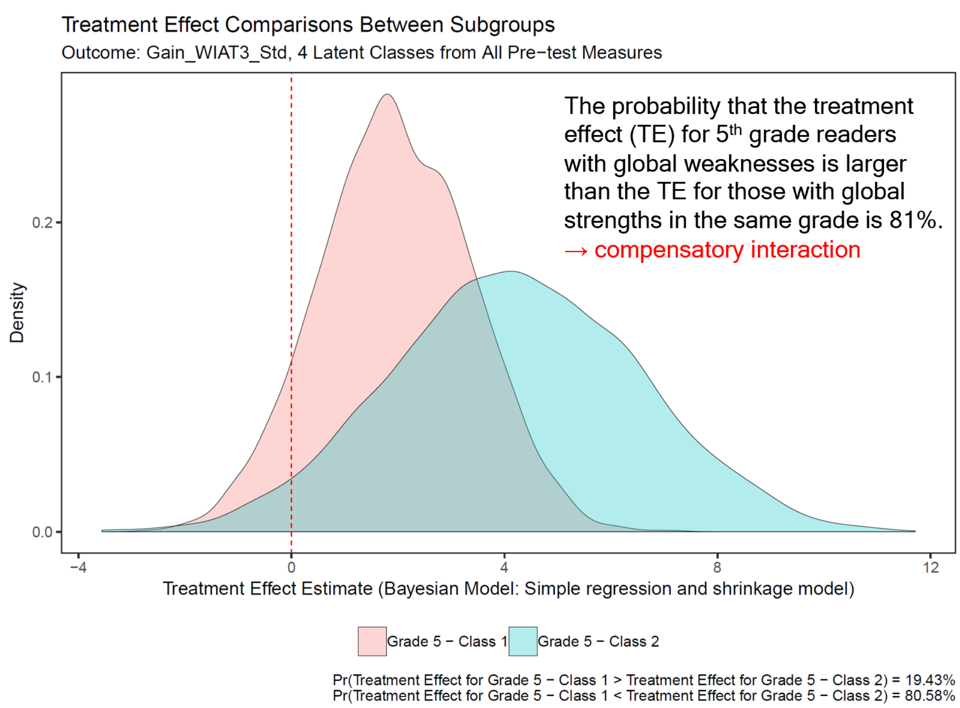


Figure 4-1. Posterior distribution of subgroup effects on WIAT3_std gain score (from the subset of the Wechsler Individual Achievement Test-Ⅲ)

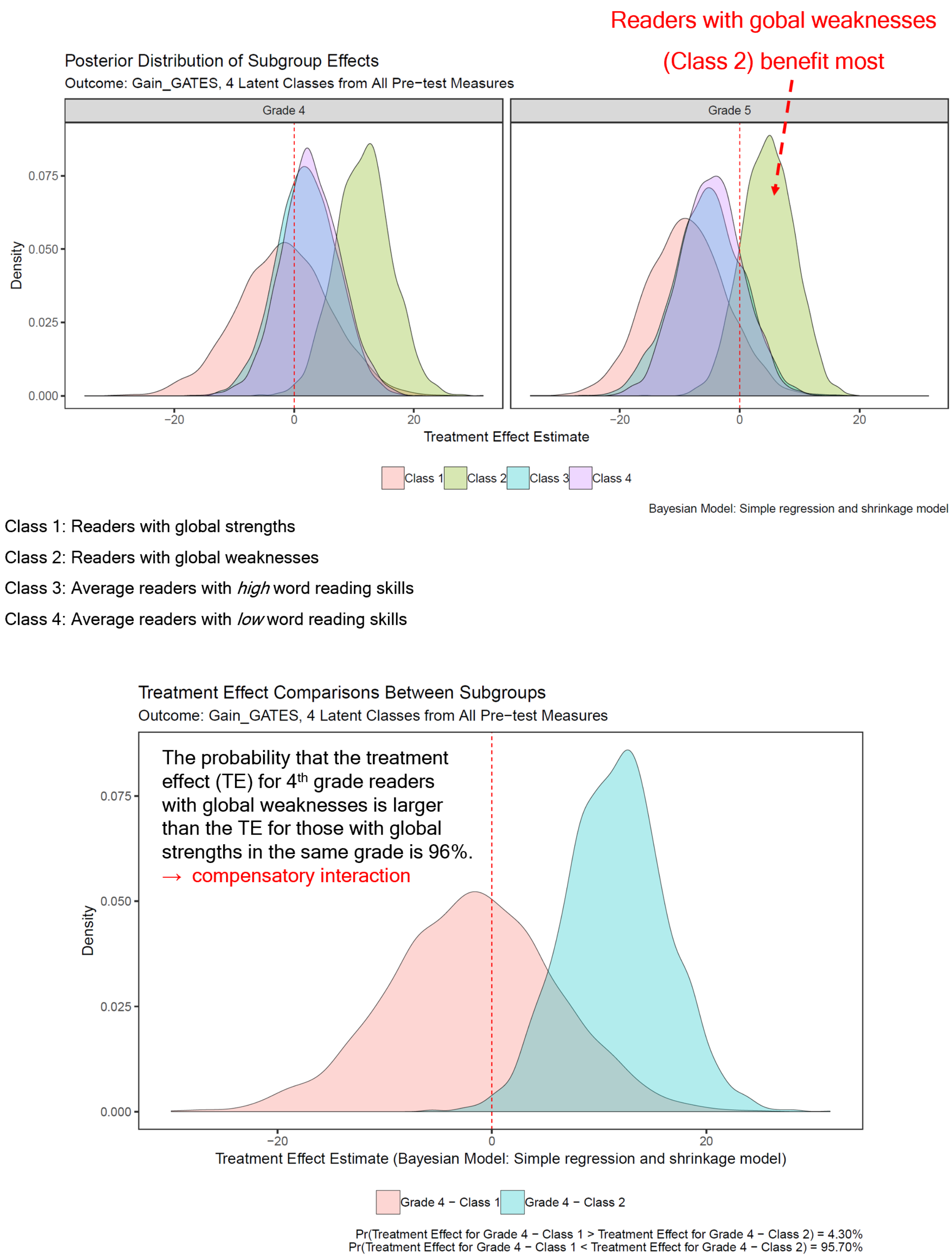


Figure 4-2. Posterior distribution of subgroup effects on *GATES* gain score: The Gates-MacHinitie Reading Tests-4

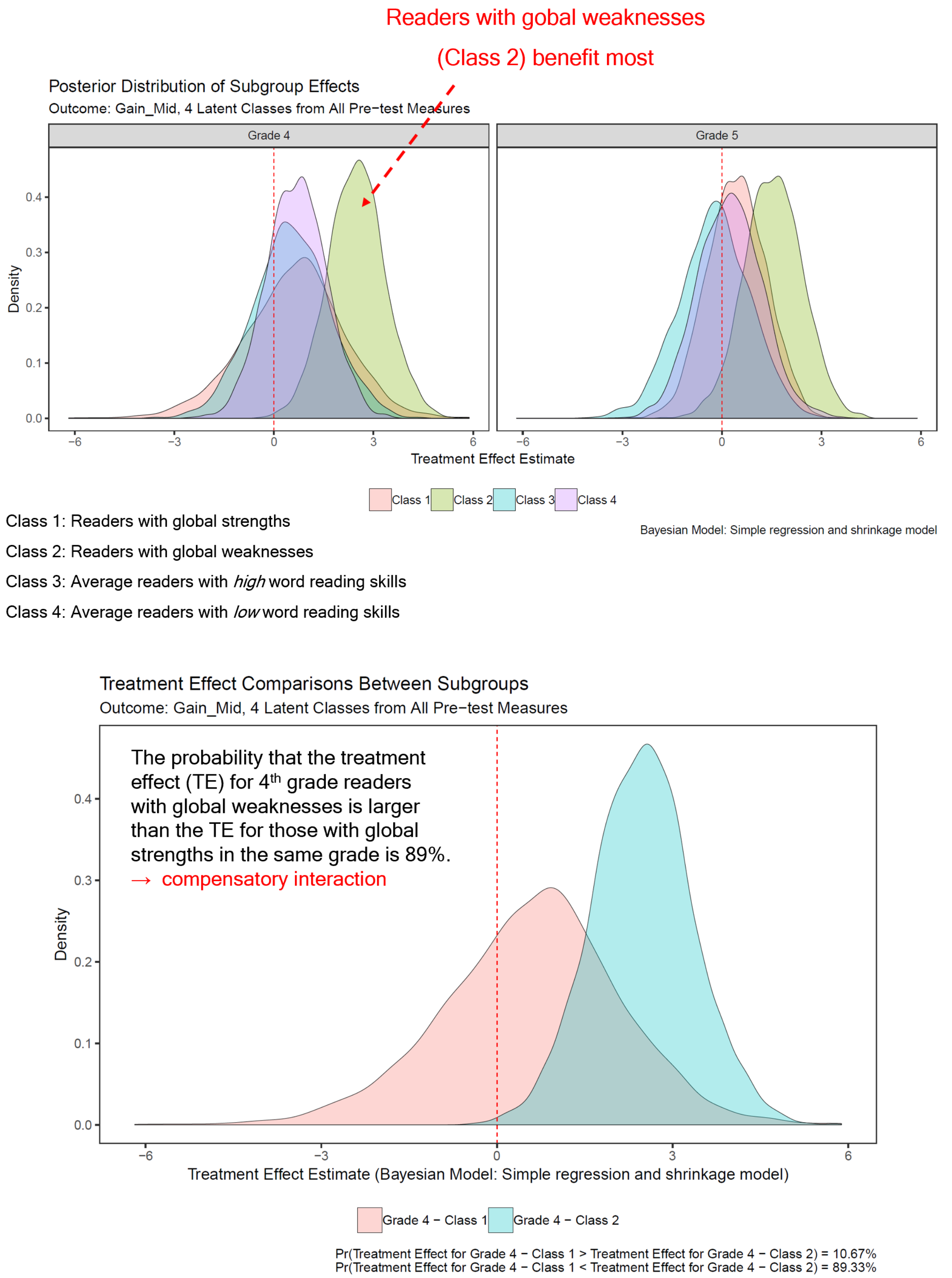
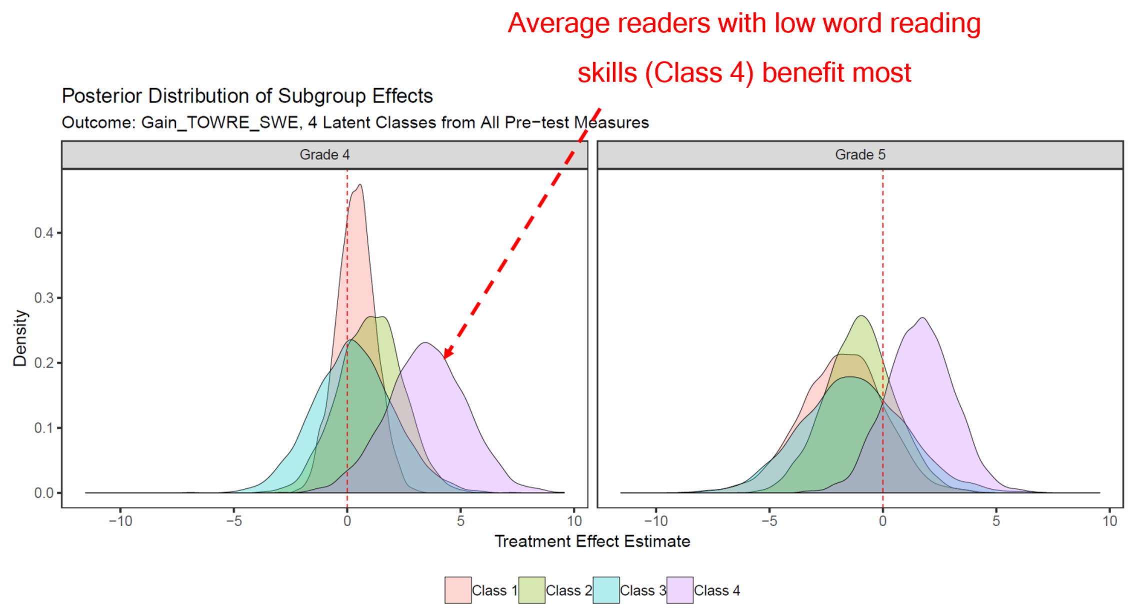


Figure 4-3. Posterior distribution of subgroup effects on *Mid* gain score*: Mid-Transfer Test of Reading Comprehension*



Class 1: Readers with global strengths

Class 2: Readers with global weaknesses

Class 3: Average readers with *high* word reading skills

Class 4: Average readers with *low* word reading skills

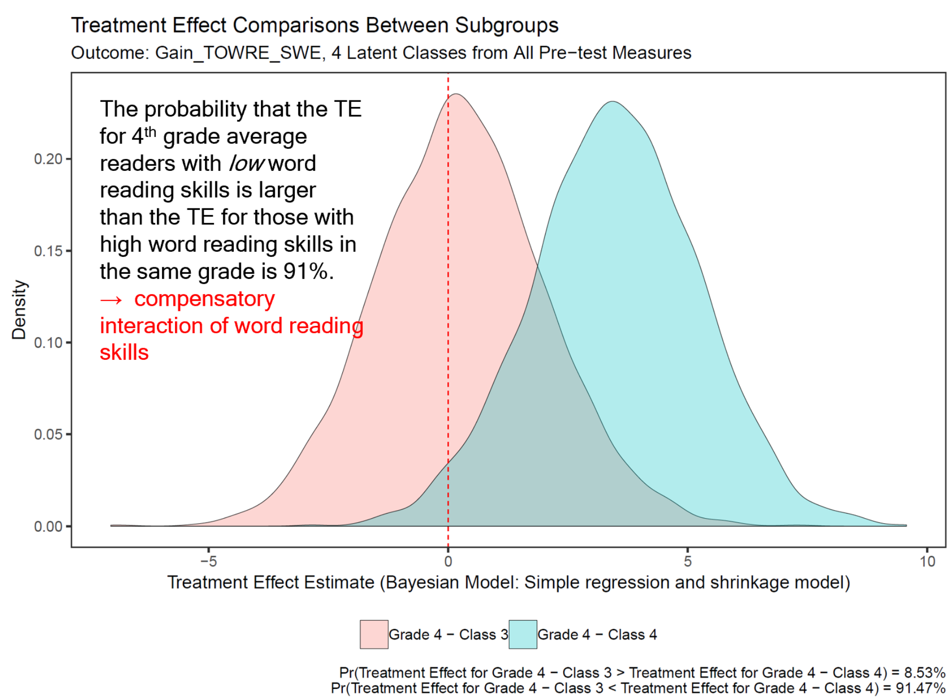


Figure 5. Posterior distribution of subgroup effects on *TOWRE_SWE* gain score*:* The Sight Word Efficiency subset of the Test of Word Reading Efficiency-2