**ED255C**
**Assignment#6**

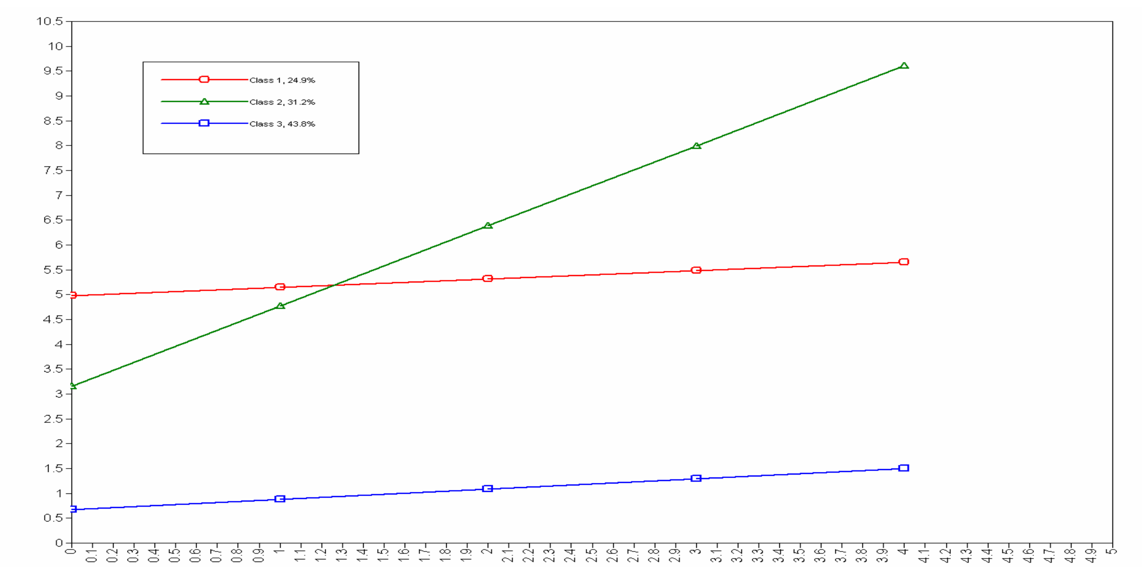
## For Whom Is The Intervention Effective?
## Assessment of Intervention effect on Reading Achievement using Growth Mixture Modeling

### Introduction

This report is a continuation of Assignment 5, which analyzed reading achievement data generated by the Mplus Monte Carlo facility, which consists of 512 subjects in the control group and 488 in the intervention group. Through analyzing the control group separately in Assignment 5, a three-class growth mixture model (GMM) was selected to establish the normative reading achievement growth patterns of subgroups before intervention. The three classes established were 1) a class with a high baseline which grew slowly, 2) a class with a medium baseline which grew rapidly, and finally, 3) a class with a low baseline which grew slowly (Figure 1).

Given the normative growth patterns of the three subgroups, it would be of interest to examine how interventions would affect reading achievement pattern for each subgroup. Hence, this time, I conducted a growth mixture model of the control and intervention groups jointly to assess the intervention impact and, especially, to focus on investigating for whom the intervention is effective. Regarding the intervention effect on the academic achievement of students, there is an argument about how the effect would show up. Some researchers hypothesize that the intervention benefits mostly the low-scoring students, while others hypothesize that the intervention is not powerful enough for the low-scoring students and will be more beneficial to students who are at a somewhat higher initial level. Therefore, I tested which hypothesis is more appropriate by examining who receives the most benefit from the intervention.

**Figure 1 Normative growth patterns : Estimated mean curves of 3 classes within the control group**



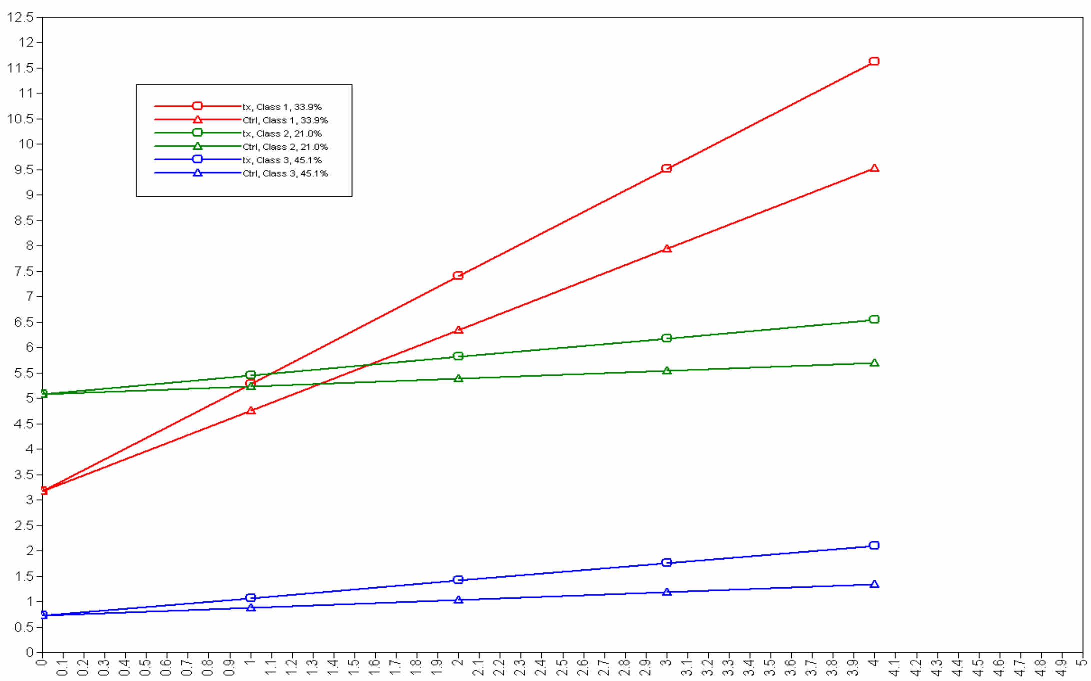
## Assessment of Intervention Effects

*Three class Growth Mixture Model without Covariates and Distal outcome*

Based on the three-class GMM from the control group analysis, a model holding the effect of intervention on the growth rate factor invariant across classes was first compared to amodel allowing the effect to be class-specific. At this step, a covariate was not included in the model. The likelihood ratio chi-square difference test supported the model with the class-varying effect of intervention on the linear growth slope factor ($\chi^2_2 = 7.798$, $p<0.05$) [1]. The three-class GMM with the class-varying intervention effect, thus, was selected and its parameter estimates are shown in Table 1. In the three-class GMM, the high baseline class, the medium baseline class and the low baseline class consisted of 21.0%, 33.9% and 45.1% of the sample, respectively.

The estimated mean curves for the three classes (Figure 2) clearly shows that the class with a medium baseline seems to benefit the most from the intervention. The growth rate of reading achievement in the intervention group for this class dramatically rises across time, so much that the difference in the means of the growth slope factor between the intervention group and the control group for this class appears to be the widest of any class. Specifically, the difference in the means of the growth slope is 0.524, which is significantly different from zero. It was also found that, in the class with a low baseline, the average growth slope for the intervention group was higher by 0.191 versus the control group, indicating that there is a significant intervention effect in the low baseline class. On the other hand, the class with a high baseline which grew slowly did not show any intervention effect. Therefore, I can conclude that the intervention seems to work the best for those who are at a somewhat higher initial level.

**Figure 2 Estimated mean curves of intervention versus control group for three classes**




[1] The class-invariant model yielded a loglikelihood value of -10327.404 with 16 parameters. In comparison, the class-varying model had a loglikelihood value of -10323.505 with 18 parameters.

**Table 1 Parameter estimates for 3 class model**

Model:

$$y_{it} = \eta_{0i} + \eta_{1i} a_t + \varepsilon_{it}$$
$$\eta_{0i} = \alpha_{0k} + \zeta_{0i}$$
$$\eta_{1i} = \alpha_{1k} + \gamma_{1k} I_i + \zeta_{1i}$$
$$V(\zeta \mid class\_k) = \Psi_k$$
$$V(\varepsilon \mid class\_k) = \Theta_k$$
$$p(c_{ik}) = \frac{e^{\alpha_{ck}}}{\sum e^{\alpha_{ck}}}$$

Reading Achievement Growth Estimates

| **Parameter** | **High Baseline with slow growth (S.E)** | **Medium Baseline with rapid growth (S.E)** | **Low Baseline with slow growth (S.E)** |
|---|---|---|---|
| $\alpha_0$ | 5.078(0.124) | 3.169(0.094) | 0.719(0.077) |
| $\alpha_1$ | 0.153(0.105) | 1.590(0.093) | 0.478(0.044) |
| $\gamma_1$ | 0.214(0.146) | 0.524(0.107) | 0.191(0.078) |
| $V(\zeta_0)$ | 1.323(0.114) | 1.323(0.114) | 1.323(0.114) |
| $V(\zeta_1)$ | 0.478(0.044) | 0.478(0.044) | 0.478(0.044) |
| $V(\varepsilon_1)$ | 0.331(0.058) | 0.331(0.058) | 0.331(0.058) |
| $V(\varepsilon_2)$ | 1.062(0.060) | 1.062(0.060) | 1.062(0.060) |
| $V(\varepsilon_3)$ | 1.624(0.083) | 1.624(0.083) | 1.624(0.083) |
| $V(\varepsilon_4)$ | 2.288(0.146) | 2.288(0.146) | 2.288(0.146) |
| $V(\varepsilon_5)$ | 2.291(0.205) | 2.291(0.205) | 2.291(0.205) |

Latent class Estimates

| **Parameter** | **Estimate** | **S.E** |
|---|---|---|
| $\alpha_{c1}$ | -0.286 | 0.102 |
| $\alpha_{c2}$ | -0.766 | 0.110 |
| $\alpha_{c3}$ | 0.000 | (fixed) |

*Three-Class Growth Mixture Model with Covariates and Distal Outcome*

A covariate, the poverty status of the student’s family, was added to the previous three-class growth mixture model. By comparing the model witha class-invariant covariate effect on growth factors versus the model with a class-varying covariate effect, the likelihood ratio test suggested that allowing the covariate effect to vary across classes did not improve the model( $\chi_4^2 = 4.864$ , p>0.05) . Therefore, the effect of the covariate on growth factors was held invariant across classes.

When the three-class GMM included a negative distal outcome, the likelihood ratio test suggested that the model which allows the probability of distal outcomes to vary between the low baseline class and the other two classes appeared to fit the data best ( $\chi_1^2 = 43.68$ , p<0.001, Table 2). Therefore, the three-class

GMM with a class-invariant covariate and a class-varying distal outcome has been selected as my final model.

**Table 2 Class-Invariant Model With A Distal Outcome Versus Class-Variant Model With A Distal Outcome**

| Model | Loglikelihood | #parameters | BIC | Entrophy | -2*Difference |
|---|---|---|---|---|---|
| 3 class GMM with class invariant distal outcome | -10724.616 | 28 | 21642.649 | 0.746 | |
| 3 class GMM with 1 class varying distal outcome | -10702.776 | 29 | 21605.876 | 0.757 | 43.68 |
| 3 class GMM with all class varying distal outcome | -10701.915 | 30 | 21611.063 | 0.758 | 1.722 |

Regarding the effect of the covariate, the poverty status of the student's family, on growth factors, it was found that the poverty status of the student's family is significantly and negatively associated with the initial growth factor. This implies that groups of students with a greater level of poverty appear to have lower initial status than students with a smaller level of poverty. However, poverty status did not appear to influence the growth rate. Relative to the high baseline class, the odds of being in the low baseline class are significantly increased by having a greater level of poverty (the odds = $e(0.853) = 2.35$).

Previously, the control group analysis found that the probability of the distal outcome occurrence in the low baseline class was much higher than in both the high and medium baseline classes. The joint analysis also produced the same results. The odds of the low baseline class having a negative distal outcome are 4.71 times larger than for the high or the medium baseline classes indicating that the negative distal outcome is more likely happen to those who are in the low baseline class than those who are in the high or the medium baseline classes.

The estimated odds ratios indicate positive intervention effects on the negative distal outcome in the high, medium and low baseline classes. Table 3 shows the ratios of the odds of having a negative distal outcome in the intervention group relative to the odds in favor of having a distal outcome in the control group for the three classes. Since the odds ratios are smaller than 1 for each class, the odds of having a negative distal outcome in the intervention group are smaller than in the control group for each class. All of the classes show a significant relationship between intervention status and a distal outcome since the 95% confidence intervals for odds ratios for classes did not include 1. Hence, I can conclude that the intervention seems to reduce the risk of having a distal outcome for each class.

**Table 3 Odds ratios of Distal outcome for Intervention versus Control group**

| Class | OR | 95% Confidence interval |
|---|---|---|
| High Baseline Class | 0.314 | (0.139, 0.710) |
| Medium Baseline Class | 0.326 | (0.158, 0.670) |
| Low Baseline Class | 0.351 | (0.227, 0.351) |

## Discussion

This report has discussed growth mixture modeling with a focus on detecting different intervention effects for individuals belonging to different trajectory classes. The joint analysis of the control and intervention groups using a three-class growth mixture model found that there was an overall positive effect of intervention on the reading achievement of all subgroups which were obtained by examining the developmental trajectory patterns of the sample. Among the subgroups, students in the class with a medium baseline, in particular, seem to have the most benefit from intervention because the average growth rate of the intervention group is much higher than that of the control group. Although intervention also positively influences the reading achievement in the low baseline class, it seems that the effect is not powerful relative to the intervention effect in the medium baseline class. Therefore, I conclude that the hypothesis that the intervention effect is more beneficial for students who are at a somewhat higher initial level than students who are at low initial level appears to be appropriate for this reading achievement data. Moreover, this implies that, for designing future interventions, we should consider implementing different interventions for students belonging to low and high baseline classes given that the intervention in this study was found to be less powerful for those two classes.