Investigation of Reading Development Patterns for Students in Early Grades Using Latent Transition Analysis

Objectives

Response to Intervention (RTI) has been widely implemented by schools as a way to maximize efficient use of resources and effective instruction (Fuchs, & Fuchs, 2006; Wright, 2005). A critical component for successful RTI implementation is monitoring student progress. Tracking students' academic growth helps teachers (a) better understand students' growth patterns, (b) classify students into appropriate instructional groups, and (c) determine the intensity of academic support needed for students in different groups. Although the importance of understanding students' within-year growth has been heavily emphasized in the RTI framework, understanding of long term student growth is not emphasized nearly as much. In this investigation of reading development patterns for students in early grades, we answer the following research questions using Latent Transition Analysis:

RQ1: What is the average initial performance and growth for students in grades 2 through 4 on the easyCBM Passage Reading Fluency (PRF) assessment?

RQ2: Are there distinctive patterns of initial performance and growth present in the data for each grade?

RQ3: Are there any distinctive reading development patterns over time?

RQ4: What is the relationship between the reading development patterns and students' special education and English language learner status?

Theoretical Framework

As RTI has continued to gain popularity as a multi-tier instructional framework, the use of curriculum based measurement (CBM) has also increased as a way to measure student academic progress (Fuchs, Fuchs, Hosp, & Jenkins, 2001; Jenkins, Graff, & Miglioretti, 2009). Oral Reading Fluency (ORF) is a measure of students' ability to read connected text with speed and accuracy. Because ORF is relatively easy and quick to administer and has demonstrated strong predictive power of later reading skills (Reschly, Busch, Betts, Deno, & Long, 2009), it has been one of the most widely used benchmark and progress monitoring measures (Petscher & Kim, 2011).

Numerous research studies show that ORF is a strong predictor of reading comprehension (Fuchs, Fuchs, Hosp, & Jenkins, 2001; Kim, Petscher, Schatschneider, & Foorman, 2010). However, there has been relatively little effort to understand the growth of ORF (Kim, Petscher, Schatschneider, & Foorman, 2010; Nese, Biancarosa, Anderson, Lai, Alonzo, & Tindal, 2012). Furthermore, most of these studies investigated within-year ORF growth with small numbers of students and relatively simple analytic techniques (Betts, Bolt, Decker, Muyskens, & Marston, 2009; Fuchs, Fuchs, & Hamlett, 1993; Jenkins, Graff, & Miglioretti, 2009) which may not be robust enough to accurately model complex patterns of growth that could emerge across academic years. Understanding within-year growth in ORF, while helpful for modifying instruction for students, may not predict how students develop their reading skills over multiple years. Moreover, understanding growth across multiple years could help to identify patterns of student trajectories that suggest greater levels of risk into the future.

Using the Latent Transition Analsyis (LTA) technique, we investigate whether there are homogeneous long-term reading developmental trajectories for all students, and if not, identify different groups of students demonstrating unique developmental reading trajectories. Results of this study can help teachers enhance their instructional practices by identifying different groups of students who are at unique stages of reading development and accommodate student academic needs beyond specific grade-level expectations.

Methods

easyCBM Passage Reading Fluency (PRF)

A type of ORF measure, the easyCBM PRF is an individually-administered one-minute timed assessment, which measures student ability to read connected narrative text accurately. The easyCBM benchmark and progress monitoring assessment system (Alonzo, Tindal, Ulmer, & Glasgow, 2006) includes 3 benchmark and 17 progress monitoring PRF measures per grade. The alternate forms are comparable in difficulty within grade, but are not vertically scaled across grades. In this study, we administered the three benchmark PRF measures in the beginning, middle, and end of two academic school years, a total of six PRF administrations.

Student Demographic Variables

In addition to easyCBM PRF scores, two student demographic variables were used as covariates in the model: English language learner (ELL) and special education (SPED) status. Due to space constraints, demographic information will be provided in the full paper.

Participants

Data used for the preliminary analysis presented in this proposal were collected during the 2009-2011 school years from two school districts in the Pacific Northwest, from students in grades 2 and 3, respectively. The final analytic sample included approximately 1,800 students in each year with at least one easyCBM PRF score in each year. Both school districts shared similar student demographic characteristics. Approximately 50% of students were female, 70% white, 10% receiving special education services, and 5% English language learners.

For the final analysis prior to the conference, data collected during 2011-2012 school year from the same students will also be included as well their demographic variables. The 2011-2012 school year data will be ready for analysis in fall of 2012.

Analytic Procedure

Latent Transition Analysis (LTA) is a longitudinal data analysis technique often used to model developmental patterns in latent (unobserved) categories (Lanza & Collins, 2008). A two step process was used to investigate students' reading developmental patterns and their transition patterns over three years. First, because the easyCBM PRF measures are not vertically scaled acorss grades, Growth Mixture Modeling (GMM) was conducted to model within-year growth separately for each year and to determine the number of latent classes that best represent the data. Based on the GMM results, LTA will be conducted to model the long-term reading growth patterns and transition patterns. Although LTA has not been conducted for the preliminary analysis, crosstabulation analysis of predicted latent class membership between year 1 (2nd grade) and year 2 (3rd grade) was conducted to demonstrate transition patterns. Figure 1 and 2 display the unconditional and conditional latent class piecewise growth curve model, respectively.

Results

A series of unconditional growth mixture models (GMM; Muthén, 2004) were conducted using maximum likelihood confirmatory factor analysis methods within Mplus version 6.0 (Muthén & Muthén, 2010) to determine whether there are distinctive within-year ORF growth trajectories. From this process, a piecewise growth curve model fit the data best, and was selected as a final functional form. As Figure 1 displays, two growth parameters were estimated for each year to represent growth between fall and winter as well as winter to spring. A piecewise growth model does not assume linear growth across all three time points (from fall to spring). Instead, it estimates two linear growth components: from fall to winter and from winter to spring.

To determine the number of latent classes that best fit the data, (a) relative model fits were compared using AIC, BIC, and ABIC fit indices (if accepted for presentation, we will also discuss the Integrated Classification Likelihood measure of model fit outlined by McLachlan and Peel (2000) which has shown positive results in estimating the number of latent classes but has yet to incorporated into educational/psychological literature), (b) Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (VLMRLRT) was conducted (if accepted for presentation, we will explore the Bootstrap Likelihood Ratio Test by McLachlan and Peel (2000) to introduce this promising procedure), and (c) the practical implications of each latent class were evaluated. It is important to note that we are presenting the results from the preliminary analysis for the first two research questions using the first two years of data. For the conference presentation, results from the final analysis including all three years of data (collected from 2009-2012 school years) will be presented.

Research Question 1

A single-class unconditional latent class piecewise growth curve model (Figure 1) was fit to the data to determine the average fall performance and growth from fall to winter as well as from winter to spring in year 1 and year 2 separately.

For year 1, students' estimated average initial performance in the fall of Grade 2 was 60.34 words correct per minute (WCPM) with an average growth of 15.76 WCPM from fall to winter and 22.89 WCPM from winter to spring. For year 2, students' estimated average initial performance in the fall of Grade 3 was 87.74 WCPM with an average growth of 31.70 WCPM from fall to winter and 0.06 WCPM from winter to spring.

Research Question 2

To address the second research question, a series of unconditional GMM with two to seven latent classes were fit to the year 1 and 2 data. When comparing the model fit indices as well as the VLMRLT results, the seven and six-class solutions were statistically the best fitting models for year 1 and 2 data, respectively. However, four classes from each year's data subsumed a very small proportion of students (less than 5%), and didn't seem to have meaningful interpretation of these classes; therefore, the four-class GMM for year 1 and three-class GMM for year 2 were selected. Tables 2 displays results of model fit comparisons.

For year 1 (2nd grade), there were four distinctive groups of students. The first group of students ("high achieving") was represented by 3% of the sample and had the highest estimated initial performance (M = 186.80 WCPM). The second group of students ("fast growing") was represented by 51% of the sample and made constant growth between fall to winter (M = 26.44 WCPM) as well as winter to spring (M = 23.37 WCPM). The third group of students ("low-risk") was represented by 12% of the sample. Their average initial performance was 119.59 WCPM, and they made steep growth from winter to spring (M = 27.88 WCPM). The last group ("high-risk") was represented by 34% of the sample. Although they made noticeable growth from winter to spring (M = 23.37 WCPM), their average initial performance was extremely low and did not improve fast enough to catch up with other students.

For year 2 (3rd grade), there were three distinctive groups of students. The first group of students ("high achieving") was represented by 9% of the sample in the data and had the highest estimated initial performance (M = 152.30 WCPM). The second group of students ("low-risk") was represented by 22% of the sample. Their average initial performance was 106.26 WCPM, and they made steep growth from fall to winter (M = 51.05 WCPM). The last group of students ("high-risk") was represented by 68% of the sample. Their average initial performance was 71.02 WCPM, and they made noticeable growth from fall to spring (M = 26.96 WCPM), but their growth flattened out from winter to spring. Table 3 describes each latent class for years 1 and 2. For the conference presentation, all four research questions will be answered using three years' worth of longitudinal data. Figures 3 and 4 display the growth patterns for each class for year 1 and 2.

Approximately 96% of students in the "high risk" group in year 1 were also in the "high risk" group in year 2. About 50% of students in the "high achieving" and "low risk" groups in year 1 stayed in the same categories in year 2. For students who were in the "fast growing" group in year 1, approximately 29% were classified as "low risk" in year 2; however, 64% were classified as "high risk". Table 4 displays the complete result of cross-tabulation analysis of predicted latent class membership between year 1 (2nd grade) and year 2 (3rd grade).

Significance of Study

In this study, the initial performance and growth rates of easyCBM PRF for students in the primary grades were estimated using GMM to examine homogeneity of the growth trajectory. The results of preliminary analyses suggest that in year 1 (2^{nd} grade), the four-class model (high achieving, fast growing, low-risk, and high-risk) best represents the data. In year 2 (3^{rd} grade), the three-class model (high achieving, low risk, and high-risk) seems to represent the data the best.

Although preliminary, results suggest that students' reading developmental trajectories may not be homogeneous, supporting the need for Latent Transition Analysis. Given that students' reading instruction typically transitions from "Learning to read" to "Reading to learn" during grades two to four, it is anticipated that results from the three year longitudinal data will provide more in-depth information about students' long-term reading developmental trajectories.

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Table 1
Descriptive Statistics of easyCBM PRF Measures

	n	Mean	*SD*	Range
Year1 fall PRF	1772	60.70	41.50	254
Year1 winter PRF	1797	76.14	40.50	219
Year 1 spring PRF	1809	99.07	44.78	242
Year1 Δ fall to winter	1753	15.84	18.18	196
Year 1Δ winter to spring	1791	22.91	16.73	191
Year2 fall PRF	1788	88.15	41.06	267
Year2 winter PRF	1787	119.80	45.73	262
Year 2 spring PRF	1793	119.30	44.83	325
Year2 Δ fall to winter	1778	31.75	18.79	135
Year 2 Δ winter to spring	1768	0.07	17.86	137

Table 2

Fit Indices of Growth Mixture Models for Year 1 and Year 2

Classes	Parameters	Year 1					Year 2				
		AIC	BIC	ABIC	Entropy	LRT*	AIC	BIC	ABIC	Entropy	LRT
1	7	49074.54	49113.07	49090.83			49125.94	49164.47	49142.23		
2	11	48419.63	48480.18	48445.24	0.94	<0.001	49019.56	49080.10	49045.15	0.66	0.00
3	15	48310.99	48393.56	48345.90	0.68	0.00	48906.59	48989.15	48941.49	0.65	0.00
4	19	48126.45	48231.03	48170.67	0.74	0.00	48859.75	48964.32	48903.96	0.71	0.05
5	23	48019.39	48145.99	48072.92	0.80	0.02	48820.31	48946.90	48873.83	0.70	0.03
6	27	47958.38	48107.00	48021.22	0.79	0.03	48792.01	48940.62	48854.84	0.73	0.31
7	31	47915.06	48085.69	47987.21	0.80	0.13					

Note. LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test for k versus k-1 classes.

* Indicates *p*-values for LRT test.

Table 3
Description of Each Latent Class

Class	Year 1				Year 2			
	Proportion	Mean Intercept	Growth from F-W	Growth from W-S	Proportion	Mean Intercept	Growth from F-W	Growth from W-S
High achieving	0.03	186.80	-31.93	26.27	0.09	152.30	15.77	8.42
Fast growing	0.51	61.18	26.44	23.37	--	--	--	--
Low-risk	0.12	119.59	3.54	27.88	0.22	106.26	51.05	-13.53
High-risk	0.34	28.50	9.23	20.28	0.68	71.02	26.96	3.81

Note. LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test for k versus k-1 classes.

Table 4

Result of Crosstabulation Analysis of Predicted Latent Class Membership Between Year 1 (2nd grade) and Year 2 (3rd Grade)

Year 1 Class	Year 2 Class			Total
	Low risk	High risk	High achieving	
High achieving	20 (37%)	3 (5.6%)	31 (57.4%)	54 (100%)
High risk	21 (3.4%)	596 (96.4%)	1 (0.2%)	618 (100.0%)
Low risk	100 (47.6%)	44 (21%)	66 (31.4%)	210 (100%)
Fast growing	266 (28.5%)	600 (64.3%)	67 (7.2%)	933 (100%)

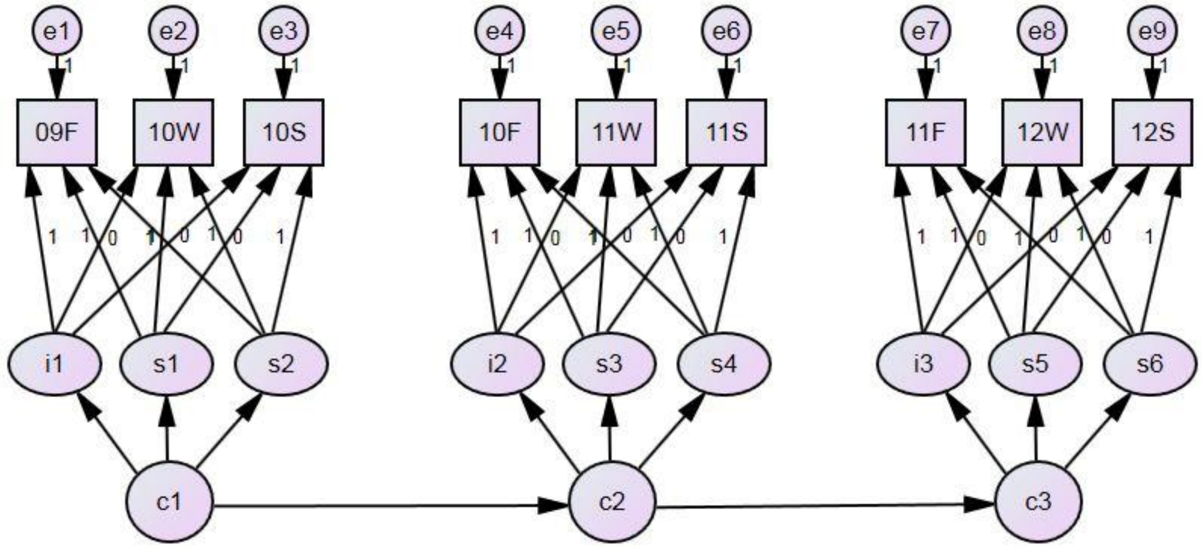

Figure 1. Latent Transition Model without Covariates

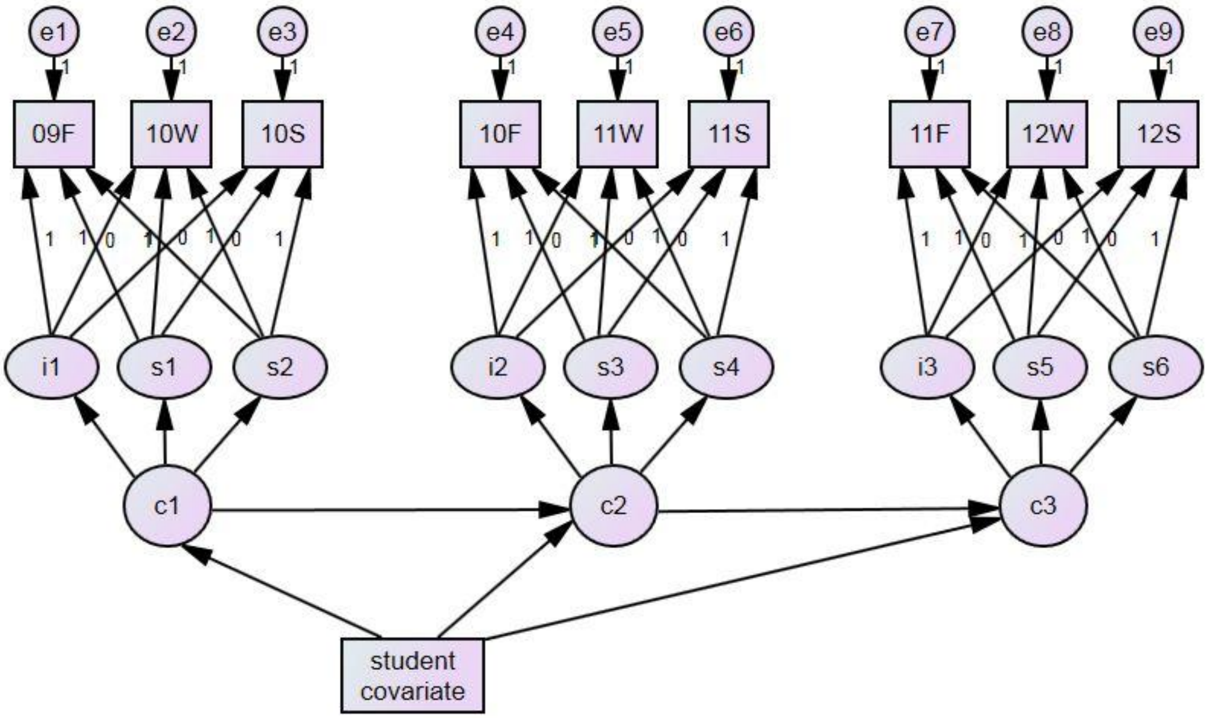

Figure 2. Latent Transition Model with Covariates (to be estimated)

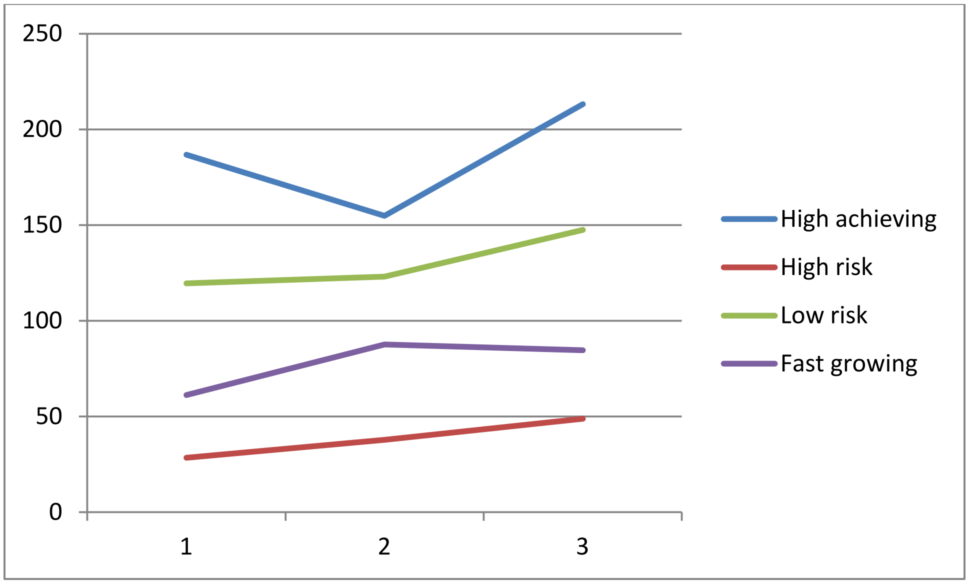

Figure 3. Within-year Growth for Year 1 (2nd Grade)

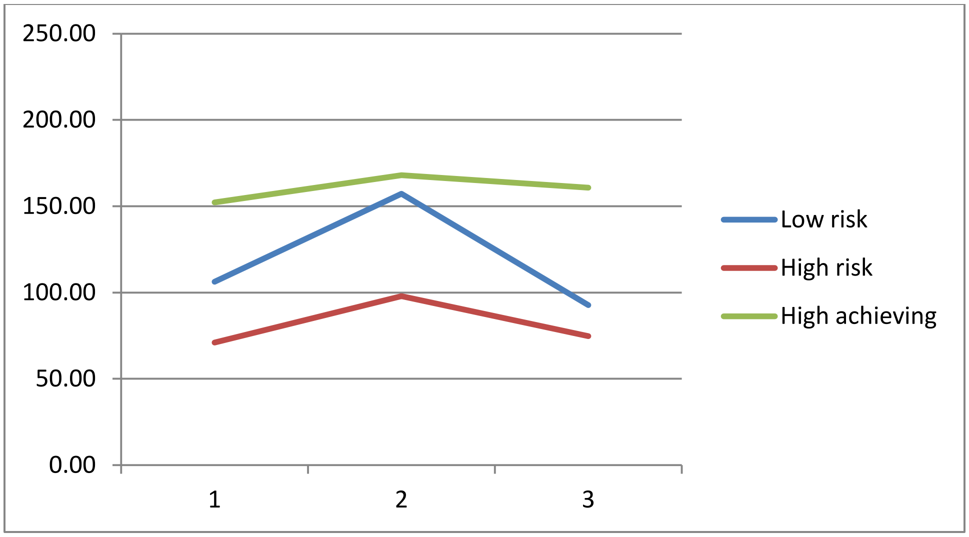

Figure 4. Within-year Growth for Year 2 (3rd Grade)