## **Cohort and** Content Variability in Value-Added Model School Effects

Daniel Anderson Joseph Stevens University of Oregon

## Introduction

#### Value added Models, or VAMs:

Are intended to measure the effect of teachers and/or schools on students' achievement

Establishing the stability (reliability) of the models is prerequisite to establishing validity, which is foundational for their use in highstakes policy applications

#### Study purpose

Evaluate the stability of school-level VAM estimates across cohorts and content area.

## **Cohort effects**

VAMs assume estimates do not depend on the specific sample of students modeled.

Typically, only one year of data is included in estimates.

Estimates may then be representative of policy or implementation effects

Student mobility is high in many schools

If school effects do depend, in part, on sampling variability, then the validity of estimates is threatened

## **Content effects**

Little research has explicitly explored the difference in school rankings by the content area.

Much research has investigated school effects in a single content area, while ignoring others (Raudenbush and Bryk, 1986; Raudenbush and Willms, 1995)

Should we expect schools to have the same effect across content areas? What does it mean if different effects are observed?

## Research Questions

What is the stability of school effect estimates across cohorts and content area (reading and math)?

What proportion of the variance in students' scores is attributable to school, cohort, or content facets?

How does the number of cohorts modeled impact the reliability of school effect estimates?

## Methods: Sample

#### **Demographics**

Prop	Proportion		
nonWhite	35		
SWD	12		
Female	50		
FRL	50		

Operational statewide accountability data

Three cohorts of students matched longitudinally across Grades 3-5 (approximately 27000 students per cohort)

727 schools, with an average of 122.44 students per school (SD = 95.17)

# Analysis plan

Fit a VAM to each cohort of students in each content area

Explore changes in schools' normative rank across models

Fit a combined model across cohorts

Use Generaliziability Theory to (a) estimate the reliability of school effects, and (b) project reliability, given a change in the number of cohorts modeled.

#### Basic schooleffects model

 $RIT_{ig} = 1 + 1(g4) + 2(Pr \times g3_4) + 3(Pr \times g3_5) + 4(Pr \times g3_5$ 

 $RIT_{ig}$ : State test score in Grade g for student i (includes both students' Grade 4 and Grade 5 data)

: Model intercept (mean Grade 5 scores, given average Grade 3 and 4 scores)

g4: Dummy code indicating if the outcome was in Grade 4 (rather than Grade 5)

Pr: Students prior state test score

 $g3_4$ : Grade 3 prior state test score, Grade 4 outcome

 $g3_5$ : Grade 3 prior state test score, Grade 5 outcome

 $g4_5$ : Grade 4 prior state test score, Grade 5 outcome

 $r_i$  and  $u_j$ : Random by-student and by-school variation

$$r_i \sim N(0, stu)$$
  
 $u_j \sim N(0, sch)$ 

 $\begin{array}{l} e_{ij}\text{: Unmodeled residual variance} \\ e_{ij} \sim N(0, \ _{e}) \end{array}$ 

# Breaking the model apart

### **Grade 4 outcome** RIT<sub>i4</sub> = $\dot{-}_{1}(g4) + _{2}(Pr \times g3_4) + r_i +$

#### **Grade 5 outcome** $\operatorname{RIT}_{i5} = \stackrel{\frown}{+}_{3}(\operatorname{Pr} \times g3_5) + r_i + u_j + e_{ij}$ $\operatorname{RIT}_{i5} = \stackrel{\frown}{+}_{4}(\operatorname{Pr} \times g4_5) + r_i + u_j + e_{ij}$

### Fixed-effects portion of the model



Note the residual variances were constrained to be equal

## **Combined model**

 $(g4) + _{2}(Pr \times g3_{4}) + _{3}(Pr \times g3_{5}) + _{4}(r_{i} + u_{j} + v_{c} + v_{c}u_{j} + e_{ij})$ 

 $v_c$ : Random cohort variation  $v_c \sim N(0, _{coh})$ 

 $\begin{array}{l} v_c u_j \text{: Random cohort by school} \\ \text{variation (latent interaction variable)} \\ v_c u_j \sim N(0, \ _{cohSch}) \end{array}$ 

## **G-Theory**

Relative reliability coefficient  $G = \frac{2}{\frac{\text{sch}}{2}}$   $\frac{2}{\frac{2}{\text{sch}} + \frac{2}{\frac{2}{\text{cohSch}}} + \frac{2}{\frac{2}{\frac{e}{1}}}}$ 

Absolute reliability coefficient



A priori minimal threshold for reliability: 0.90

#### Results: Schooleffect variability across cohorts (math)

- ~ 33.77% of schools did not change quartiles
- ~ 53.66%
  changed
  quartiles at
  least once
- ~ 12.57% changed quartiles

between each cohort modeled

- ~ 22.7% of schools changed more than one quartile
- ~ 3% of schools moved

#### Math Pairs Plot



from the bottom to the top quartile, or vice versa, depending on the specific cohort modeled



#### Results: Schooleffect

#### variability across cohorts (reading)



 ~ 33.71% of schools did not change quartiles



- ~ 53.11%
  changed
  quartiles at
  least once
- ~ 13.18%
  changed
  quartiles
  between each
  cohort
  modeled
- ~ 22.41% of schools

changed more than one quartile

 ~ 3% of schools moved from the bottom to the top quartile, or vice versa, depending on the specific cohort modeled

# Variability across content areas

~ 53%, 55%, and 52% of schools maintained their normative quartile

ranking between content areas, for Cohorts 08-10, respectively

~ 36% to 39% of schools changed one quartile

~ 7% to 9% of schools changed two quartiles

#### Results: G-Theory

Variance Components						
MathPercentageReadingPercentage						
2 stu	55.63	67.5	44.02	68.43		
2 sch	8.68	10.5	6.07	9.44		
2 coh	0.84	1.0	0.08	0.12		
$2^{\circ}$	., 1.51	1.8	0.84	1.30		
2 e	15.82	19.2	13.32	20.71		

G = 0.95 and 0.96 for reading and math, respectively  $\Phi = 0.92$  and 0.95 for reading and math, respectively

Majority of variance associated with students, followed by unmodeled variance

Schools next most important facet

Cohort and cohort by school variance negligible, relative to the whole

## **Results: D-Study**



#### School Effect Reliability Estimates by Cohort Inclusions

### Discussion

VAMs applied in high-stakes policy settings generally assume the estimates are independent of sampling variability.

> Results of this study suggest high variability depending on the specific cohort of students modeled

Generally, a single number is used to quantify the school effect

Results of this study indicate a more nuanced and multidimensional representation may be more appropriate

Projected reliability was moderate when a single cohort was modeled

Reliability increased dramatically with the inclusion of even one additional cohort

# Limitations and future directions

This study investigated "pure" cohort effects, but annual estimates may be more reflective of how the models are applied in practice.

What's the year-to-year stability?

Unclear the extent to which changes in school ranks were attributable to sampling variability versus "true" changes in school functioning

School persistence was not modeled directly

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Correspondence concerning this manuscript should be addressed to Daniel Anderson, IES Post-Doctoral Research Fellow, Center on Teaching and Learning, University of Oregon. Email: daniela@uoregon.edu /