## Revisiting Options for Measuring Teacher and School Contributions to Student Growth with End-of-Course Assessments

Student Growth Implementation Committee Meeting
February 11, 2015

## Agenda

- 9:00-9:15 Welcome, Agenda Overview: Jason Gaitanis, FLDOE, Ronda Bourn, Chair, SGIC
- 9:15-10:00 FLDOE Updates: Jason Gaitanis, FLDOE
- 10:00-11:00 End of Course Model Options: Eric Larsen, AIR
- 11:00-11:15 Break
- 11:15-12:00 End of Course Models Continued
- 12:00-12:30 Next steps


## History/Background - Going Beyond FCAT Value-Added Models

- February 2012: SGIC first considered Algebra 1 EOC model (using covariate adjustment approach)
- December 2012: SGIC considered Algebra 1 EOC models by grade along with SAT10 models
- February 2013: SGIC reviewed Algebra EOC and SAT 10 models again; also considered Biology, Geometry EOC models and AP Calculus and AP English
- Recommended use of Grade 9 Algebra model; Grade 8 Algebra model optional
- September 2013: SGIC reviewed results of Algebra 1 2012-13 analysis
- December 2013: AIR re-analyzed 12-13 EOC data using additional approaches
- SGIC did not take any action at that time
- February 2015: SGIC to revisit options for measuring student growth with assessments beyond FCAT/FSA


## Goals of a Value-Added Model

 (VAM)" Goal is to control for "sorting" of students into classes

- Necessary because students are not randomly assigned into future classes
- If sorting is not controlled for, teachers will have an advantage or disadvantage based on who they teach
- Referred to as selection bias
- To measure teacher contributions to student learning, analysis should control for sorting to mitigate any effects associated with non-random assignment ("level the playing field")


## General Evaluation Criteria for VAM Models

- Questions to guide evaluation of the models:
- Do the models implement a statistical approach that reasonably estimates teacher contributions to student learning?
- The first question will be evaluated via your judgment--we will provide a model description along with benefits and risks of the different approaches
- Do the statistical results (e.g., R squared) indicate good model fit and conform to expectations?
- To be evaluated through data summarizing the model: size of variance components, r-squared, precision
- Do the results of the models show differences across different classroom populations?
- To be evaluated on the basis of statistical impact data


## Summary of Feb 2013 Model Analysis

## Summary of Other Models

|  | Biology EOC (2011-12) | $\begin{gathered} \text { Geometry EOC } \\ (2011-12) \end{gathered}$ | SAT-10 Math (2010-11) | $\begin{gathered} \text { A.P. } \\ (2010-11) \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: |
| Type of statistical model | Covariate adjustment | Covariate adjustment | Covariate adjustment, no meas error control | Ordered probit, no school component |
| Prior score data used | FCAT science; FCAT science + up to 2 prior FCAT math; FCAT science + up to 2 prior FCAT reading | Alg 1 EOC; up to 2 prior FCAT math; Alg 1 EOC + up to 2 prior FCAT math | Grade 1 SAT-10 | AP English: grades 9 and 10 reading FCAT scores; AP Calculus AB: grades 7 and 8 math FCAT scores |
| Other covariates | Same as FCAT model | Same as FCAT model | Same as FCAT model | Same as FCAT model |
| Grades | 8-12 | 8-12 | 2 | All available |

## Summary of Other Models

| Current Grade | Biology EOC <br> $(2011-12)$ | Geometry EOC <br> $(2011-12)$ | SAT-10 (2010-11) | A.P. <br> $(2010-11)$ |
| :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.61 to 0.63 | 0.62 to 0.65 | 0.62 | N/A |
| Variance <br> Components | Teacher > School | Teacher > School | Teacher > School | N/A |
| Impact Data: <br> Mean Prior Score | 0.18 to 0.20 | 0.23 to 0.26 | 0.15 (0.07 w/o <br> school comp.) | 0.38 (Calculus) <br> 0.61 (English) |
| Impact Data: <br> Percent ED | -0.21 to -0.22 | -0.26 to -0.31 | -0.27 (0.15 w/o <br> school comp.) | -0.38 (Calculus) |

## Summary of 2013-14 Results

| Current Grade | $\begin{gathered} \text { Math FCAT } \\ (2013-14) \end{gathered}$ | Reading FCAT (2013-14) | Algebra I EOC Grade 9 (2013-14) | Algebra I EOC <br> Grade 8 <br> (2013-14) |
| :---: | :---: | :---: | :---: | :---: |
| R-squared | $\begin{gathered} 0.61 \text { (grade 4) } \\ \text { to } 0.71 \end{gathered}$ | $\begin{gathered} 0.66 \text { (grade 4) } \\ \text { to } 0.74 \end{gathered}$ | 0.48 | 0.48 |
| Variance Components | ```Teacher > School Math 6 & 7: School > Teacher``` | Teacher > School | Teacher > School | Teacher $=$ School |
| Impact Data: <br> Mean Prior Score | 0.05 | -0.02 | 0.07 | 0.17 |
| Impact Data: Percent ED | -0.07 | -0.04 | -0.02 | -0.09 |

## Summary of New EOC Models Presented December 2013

## New EOC Analysis (December 2013)

- Other EOC models (beyond Algebra grades 8 and 9) were originally not acted on by SGIC
- We observed "reversals" in the variance component patterns
- Impact data showed very high correlations between teacher scores and classroom composition
- R-squared values and precision were relatively low
- To address these issues, AIR experimented with new models that analyze the data in different ways
- The aim is to determine if a different modeling strategy can improve on the approach that has been used in Florida to date


## Objectives

- Following the SGIC's direction, we implemented 6 different analyses with EOC data to see if new methods can improve on previous approach
- Models 1-3: Enhanced covariate adjustment models; Model 4: Z-score; Model 5: Percent proficient; Model 6: Probability of proficiency
- Focus on grade 9 Algebra EOC in order to make comparisons to implemented/recommended model
- The primary aim is to determine if other models can improve on the covariate adjustment model approach previously used for EOC assessments


## Models 1-3: Enhanced Covariate

## Adjustment Model

- Some researchers have proposed that high school students are often sorted into different academic tracks
- If this tracking is correlated with sorting, then it would be necessary to control for course tracking to mitigate selection bias
- In Models 1-3, we control for students' prior math courses in addition to their prior test scores


## Grade 8 Math Courses of Students Taking the Algebra I EOC in Grade 9

- Algebra I (3.4\%)
- Algebra I Honors (2.5\%)
- Algebra la (5.6\%)
- M/J Intensive Mathematics (MC) (11.4\%)
- M/J Mathematics 3 (56.4\%)
- M/J Mathematics 3, Advanced (19.3\%)
- Others (1.4\%)


## Summary of Models 1-3

- Model 1:
- Control for two prior test scores
- Control for mean prior score of students in class
- School and teacher random effects
- Model 2 :
- Model 1 + prior course random effects
- Model 3:
- Model 1 + prior course fixed effects


## Summary of "Beta" EOC Models

|  | 2012-13 <br> Grade 9 <br> Algebra <br> Model | Baseline | Random <br> Effects | Fixed <br> Effects | Z-Score | Pct. Prof | Prob. <br> Prof |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.52 | 0.49 | 0.49 | 0.50 |  |  |  |
| Variance <br> Components | Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher <br> School | Teacher <br> $>$ School |  |  |  |
| Impact Data: <br> Mean Prior <br> Score | 0.058 | 0.093 | 0.095 | 0.095 |  |  |  |
| Impact Data: | -0.043 | -0.087 | -0.086 | -0.086 |  |  |  |
| Percent ED |  |  |  |  |  |  |  |

## Correlation Between Teacher VAM Scores:

Models 1-3

## Relationship Between VAM Scores



Scatter Plot Matrix

## Similar Models Were Implemented for the Geometry EOC

- Models were implemented separately for grade 9 and grade 10
- Three models were run for each grade
- The baseline model including only prior scores as covariates
- A model that includes course histories as random effects
- A model that includes course histories as fixed effects
- The conclusions form these models were the same as for the Algebra I EOC: controlling for course history adds almost no explanatory power to the models


## Introduction to Models 4-6

- These models are different from the linear covariate adjustment models used for FCAT and Algebra I
- Statistical summaries previously presented do not necessarily apply since outcomes are different
- Model 4: Z-Score Model
- How much do the teacher's students move up/down relative to other students?
- Model 5: Percent of Students Achieving Proficiency
- Model 6: Probability of Proficiency
- Measures impact of teacher on the probability the student achieves proficiency on Algebra I EOC


## Model 4: Z-Score Model

- Measure where in the overall state distribution of student scores each student's grade 8 math score falls
- Measure where in the overall distribution of student scores each student's Algebra I EOC score falls
- Compare the two for each student to determine how much the student moved up or down in the overall distribution of student scores
- Positive: moved up in the distribution
- Negative: moved down in the distribution
- Zero: stayed in the same place relative to other students


## Student EOC Scores Converted to Z-Scores



## Model 4: Z-Score Model

- Teacher's score = share of students who move up more than 0.3 standard deviations (s.d) in the distribution
- Moving from the mean to 0.3 s.d. above the mean on 2012-13 Algebra I EOC is equivalent to moving up 13 percentile points in the distribution.
- Assumes all students are equally likely to move up 0.3 s.d. conditional on their prior scores.
- Relatively difficult for students with high grade 8 scores to move up 0.3 s.d. (due to measurement error/regression to mean)
- Relatively easy for students with very low grade 8 scores to move up 0.3 s.d. (due to measurement error/regression to mean)
- Unlike Model 5 (percent achieving proficiency), Model 4 puts teachers of students with high grade 8 scores at a disadvantage


## Model 4: Z-Score Model



## Summary of "Beta" EOC Models

|  | 2012-13 <br> Grade 9 <br> Algebra <br> Model | Baseline | Random <br> Effects | Fixed <br> Effects | Z-Score | Pct. Prof | Prob. <br> Prof |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.52 | 0.49 | 0.49 | 0.50 | N/A |  |  |
| Variance <br> Components | Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher <br> School | Teacher <br> $>$ School | N/A |  |  |
| Impact Data: <br> Mean Prior <br> Score | 0.058 | 0.093 | 0.095 | 0.095 | -0.402 |  |  |
| Impact Data: | -0.043 | -0.087 | -0.086 | -0.086 | 0.173 |  |  |
| Percent ED |  |  |  |  |  |  |  |

## Model 5: Percent Achieving Proficiency

- Approach commonly associated with AYP
- Teacher rating is the share of students achieving proficiency (scoring above 399)
- Does not control for sorting
- Assumes students are randomly distributed across schools
- Does not control for prior test scores or any other covariates


## Model 5: Percent Achieving Proficiency



## Model 5: Percent Achieving Proficiency

- Teacher scores are highly correlated with students' prior scores
- Models such as this are useful in accountability systems when the emphasis is primarily based on identification of classrooms where students achieve a passing score
- These models typically provide different information about classrooms than is observed with growth models, but the percentage of students achieving proficiency is still a valuable outcome


## Summary of "Beta" EOC Models

|  | 2012-13 <br> Grade 9 <br> Algebra <br> Model | Baseline | Random <br> Effects | Fixed <br> Effects | Z-Score | Pct. Prof | Prob. <br> Prof |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.52 | 0.49 | 0.49 | 0.50 | N/A | N/A |  |
| Variance <br> Components | Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher <br> $>$ School | N/A | N/A |  |
| Impact Data: <br> Mean Prior <br> Score | 0.058 | 0.093 | 0.095 | 0.095 | -0.402 | 0.807 |  |
| Impact Data: | -0.043 | -0.087 | -0.086 | -0.086 | 0.173 | -0.378 |  |
| Percent ED |  |  |  |  |  |  |  |

## Model 6: Probability of Proficiency

- Use a student's prior test scores to estimate the probability the student will score above the proficiency cut-point
- Students with higher prior test scores have a higher predicted probability of passing
- Other covariates (SWD status, ELL status, prior course history, etc.) can be included in the model as well
- Conditional on a student's prior test scores (and possibly other covariates), we can determine whether some teachers' students are more likely to pass than other teachers' students


## Model 6: Probability of Proficiency

- Model assumes that conditional on prior test scores and other included covariates, students are randomly distributed across teachers and schools
- If on average a teacher's students had a low probability of passing, but many of these students passed the cut-off, that teacher would receive a high score
- If a teacher's students pass or do not pass about as expected, that teacher would receive an average score
- If fewer of a teacher's students passed than was expected, based on their prior test scores, that teacher would receive a low score


## Probability of Proficiency Model

Probability of Passing EOC Test Conditional on Prior Scores


## Compare Actual to Predicted

- Share of outcomes correctly predicted is one measure of model fit
- Model correctly predicts passage for $77 \%$ of students

| Pass Rates |  | Actual |  |
| :---: | :---: | :---: | :---: |
|  |  | Not Pass | Pass |
| $\begin{aligned} & \mathbf{0} \\ & \frac{0}{3} \\ & \frac{0}{8} \\ & \text { \$2 } \end{aligned}$ | Not Pass | 34678 (36.1\%) | 12620 (13.1\%) |
|  | Pass | 9117 (9.5\%) | 39612 (41.3\%) |

## Summary of "Beta" EOC Models

|  | 2012-13 <br> Grade 9 <br> Algebra <br> Model | Baseline | Random <br> Effects | Fixed <br> Effects | Z-Score | Pct. Prof | Prob. <br> Prof |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.52 | 0.49 | 0.49 | 0.50 | N/A | N/A | (Correctly <br> Predicts <br> 77\%) |
| Variance <br> Components <br> Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher $>$ <br> School | Teacher <br> School | N/A | N/A | N/A |  |
| Impact Data: <br> Mean Prior <br> Score | 0.058 | 0.093 | 0.095 | 0.095 | -0.402 | 0.807 | 0.243 |
| Impact Data: <br> Percent ED | -0.043 | -0.087 | -0.086 | -0.086 | 0.173 | -0.378 | -0.127 |

## Summary of Models 4-6

- Model 4 (Z-Score):
- Rewards teachers whose students make significant growth in the overall distribution of student scores
- Disadvantages teachers whose students have high math 8 scores
- Model 5 (Percent of Students Achieving Proficiency):
- Measures share of students who achieve proficiency
- Similar to AYP
- Disadvantages teachers whose students have low math 8 scores
- Model 6 (Probability of Proficiency):
- Measures teachers' impact on the probability a student achieves proficiency
- Has advantages similar to covariate adjustment model


## Correlations Between "Beta" EOC

 Models|  | Baseline | Random <br> Effects | Fixed <br> Effects | Z-Score | Pct. Prof | Prob. <br> Prof |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Baseline | 1 | 0.999 | 0.999 | 0.569 | 0.423 | 0.618 |
| Random |  |  |  |  |  |  |
| Effects | 0.999 | 1 | 0.99 | 0.567 | 0.424 | 0.616 |
| Fixed Effects | 0.999 | 0.99 | 1 | 0.567 | 0.424 | 0.616 |
| Pct. Prof | 0.423 | 0.424 | 0.424 | 0.007 | 1 | 0.721 |
| Z-Score | 0.569 | 0.567 | 0.567 | 1 | 0.007 | 0.489 |
| Prob. Prof | 0.618 | 0.616 | 0.616 | 0.489 | 0.721 | 1 |

## Summary

- Controlling for students' prior courses does little to improve predictive power of covariate adjustment models
- "Percent achieving proficiency" and z-score models do not control for sorting
- The benefits of the "probability of proficiency" models come close to those of the covariate adjustment models


## Summary of "Beta" EOC Models

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## Summary of 2013-14 Results

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## Summary of Other Models

- Evidence suggests FCAT and Grade 9 Algebra EOC models control effectively for selection
- Evidence is not as strong for other EOCs, SAT-10, APs
- The problem does not appear to be the functional form of the models
- There are not strong predictors for these EOCs, SAT-10, and AP that effectively control for non-random sorting


## Discussion

?<br>American institutes for research*

## Discussion

- Are these models better than alternatives available to districts?
- Does the SGIC recommend consideration of a covariate adjustment or other modeling approach for any of the following assessments?
- Geometry
- Biology
- U.S. History
- Civics
- FCAT Science
- If yes, what type of approach is recommended and with what parameters (e.g. what prior scores)?

