Introduction

As required by Education Law §3012-c, New York State teachers of mathematics and English Language Arts (ELA) in Grades 4±8 and their principals first received growth scores based on 2011±12 state tests. This document describes the models used to measure student growth for the purpose of educator evaluation in New York State for the 2013±14 school year. In 2013±14, growth models were implemented for teacher and principal evaluation in Grades 4±8 ELA and mathematics and for principals of Grades 9±12 (all grades). All models are based on assessing HDFKVWXGHQW¶V change in performance between 2012±13 and prior years and 2013±14 on state assessments compared to students with similar characteristics.

New York Education Law §3012-c requires performance evaluations for classroom teachers and building principals in New York State. Under the law, New York State is required to differentiate teacher and principal effectiveness using four rating categories: Highly Effective, Effective, Developing, and Ineffective (HEDI). Education Law §3012-c(2)(a) requires Annual Professional Performance Reviews (APPRs) resulting in a single composite teacher or principal effectiveness score that incorporates multiple measures of effectiveness. Education Law §3012-c(1) requires the results of the evaluations to be a significant factor in employment decisions, including but not limited to promotion, retention, tenure determinations, termination, and supplemental compensation. The law also provides that the results be a significant factor in teacher and principal professional development (including but not limited to coaching, induction support, and differentiated professional development).

State-provided growth scores are just **one** of the **several** measures that make up the annual professional performance reviews and count for 20 percent of an evaluation score for the 2013± 14 school year. For teachers with fewer than 50 percent of students who take state assessments in Grades 4±8 in ELA or mathematics, other comparable measures of student learning growth must be used for the state growth subcomponent, using the student learning objective (SLO) process established in state-provided guidance. Another 20 percent of educETBT 1 35.09 Tm[( )3 Tm1.29 T1 0 0 1 255.5

Content and Organization of This Report

Results presented in this report are based on 2013±14 DQGSULRUVFKRROHDUV¶GDWDZLWKVRPH comparisons to prior-year results. Technical reports describing models and full results from 2012±

Data

To measure student growth and to attribute that growth to educators, at least two sources of data are required: student test scores that can be observed over ti

possible. For the 2013±14 analyses, data from 2013±14 were used as outcomes, with prior achievement predictors coming from the three years before (going back to 2010±11). Specific tests used as predictors vary by grade and subject and are as follows:

- Grade 4 ELA and mathematics models used scores from Grade 3 in ELA and mathematics. Students were NOT included if they lacked Grade 3 scores in the same

Variable	Grades 4–8		Grades 9–12	
	ELA	Math-ematics	Regents ELA Common Core and Comprehensive ELA	Regents Integrated Algebra and Algebra 1 Common Core

Table 2. Grades 4–8 Teacher-Student Attribution Rates

Grade	Valid Student Records	Valid Student Records Attributed to at Least One Teacher	Attribution Rate
4	362,124	334,449	92%
5	364,861	335,310	92%
6	354,805	323,122	91%
7	356,610	325,221	91%
8	320,529	293,005	91%
Total	1,758,929	1,611,107	92%

Note: Student records are considered valid for the purposes of growth modeling when there are at least two consecutive years of valid assessment scores. Students can have as many as two valid records per year, one for ELA and one for mathematics.

Overall, in 2013±14, 92 percent of valid test scores were linked to at least one teacher. In 2012± 13, the overall attribution rate was 93 percent.

The attribution rate at the school level (98 percent) was the same in 2012±13 and 2013±14 (and in both years was higher than the student-teacher attribution rate).

Principal Attribution in Grades 4–8

1HZ5RUN¶VJURZWK5RGHOVPDNHXVHRIGHVWLEW reported staff assignment data in growth model reporting. The use of this staff assignment data allows results to be reported for individual principals for the grade levels to which they are assigned or across multiple schools for which a principal was responsible. Students were attributed to principals based on the school-level continuous enrollment indicator found in the assessment score files (see previous section for more information on this variable). Students at each grade level in a school who met the continuous enrollment requirement were attributed to a principal if that principal was assigned to that grade level in the staff assignment file. As with schools, note that student results were not weighted by attendance in determining a principal MGP.

Table 4 shows attribution rates for principals, which are somewhat lower than for schools.

Table 4. Grades 4–8 Principal-Student Attribution Rates

Grade	Valid Student Records	Valid Student Records Attributed to at Least One Principal	Attribution Rate
4	362,124	337,509	93%

Covariate Adjustment Model

The statistical model implemented as the MGP model is typically referred to as a covariate adjustment model (McCaffrey, Lockwood, Koretz, & Hamilton, 2004), as the current year observed score is conditioned on prior levels of student achievement as well as other possible covariates.

In its most general form, the model can be represented as:

$$\text{›ç ÜL} \quad \text{Ü}^{o} \text{ E ÃÅ}_{\text{å@5}} \text{›ç?åäÜç?å E AÜá} \qquad \textbf{[1]}$$

where Uç ü is the observed score at time t for student i, Ü is the model matrix for the student- and school-level demographic variables, º is a vector of coefficients capturing the effect of any demographics included in the model, Uç?åäÜ is the observed lag score at time t r (NÐ<sáíåá á ÷, and

SGPs

The previously described regression models yield unbiased estimates of the coefficients

For each student, we find a predicted value conditional on his or her observed prior scores and the model coefficients. To illustrate the concept, assume we find the prediction and its variance but do not account for the measurement variance in the observed scores used to form that prediction. We would form a conditional distribution around the predicted value and find the portion of the normal GLVWULEXWLRQWKDWIDOOVEHORZWKHVWXGHQW¶VREVHUYHGVFRUH7KLVLVHTXYDOHQWW

$$6*3_{g} L \pm \begin{matrix} \grave{\imath} \\ ? \P \end{matrix} B:T;@\eth$$

with $B:T;10:$ although this is readily accomplished using the cumulative normal distribution function, $0:$.

Figure 2. Sample Growth Percentile From Model

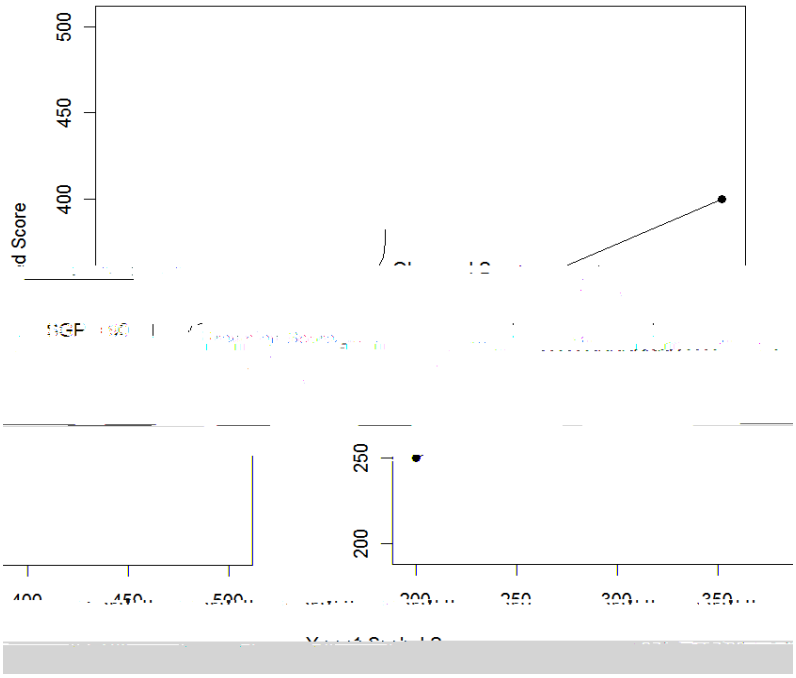
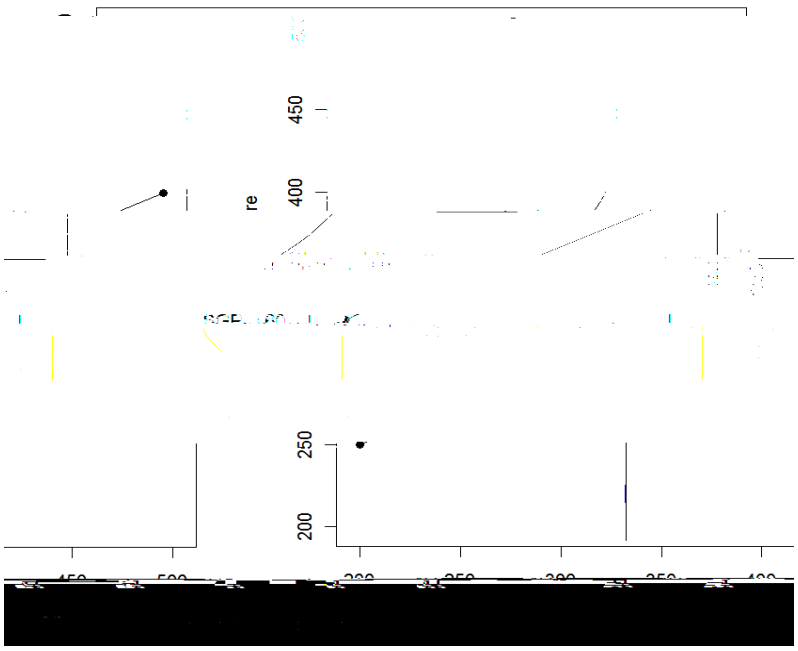


Figure 3 illustrates the same hypothetical student shown in Figure 2. Note that the observed score and predicted value are exactly the same. However, the prediction variance is larger than in Figure 2. As a result, when we integrate over the normal from $F»$ to U, the SGP is 60 and not 90 as in the previous example. This difference occurs because the conditional density curve has become more spread out, reflecting less precision in the prediction.

Figure 3. Sample Growth Percentile From Model



MGPs

Once SGPs are estimated for each student, group-level (e.g., teacher-level) statistics can be formed that characterize the typical performance of students within a group. 1HZ<RUN¶growth model Technical Advisory Committee recommended using a mean SGP for educator scores. Hence, group-level statistics are expressed as the mean SGP within a group. This statistic is referred to as the MGP.

For each aggregate unit j (FÐ<sá áå á,ŕ, such as a class/course, the statistic of interest is a summary measure of growth for students within this group. Within group j, there are <5) 2ŕ:5; á5) 2ŕ:6; áå á5) 2ŕ:Ç; ŕ=That is, there is an observed SGP for each student within group j.

Then the MGP for unit j is produced as:

$$E_h L\ P\ H\ D5Q)\ 2_{ŕ:ü;}$$

for Grades 4±8 and Grades 9±12 schools and principals and using the weighted mean

$$E_h L \frac{s}{\tilde{A}\ S_{ŕ:ü;}} Í\quad S_{ŕ:ü;} 5) 2_{ŕ:ü;} á$$

for Grades 4±8 teachers only, where $S_{ŕ:ü;}$ is a weight for student i in teacher j ¶ V FoOuDsV V EDVHGRQWKHVWXGHQW¶HQUROOPHQWDQGDWWHQGDQFH

Like all statistics, the MGP is an estimate, and it has a variance term. The following measures of variance are produced for the MGP.

The analytic standard error of the unweighted MGP (schools and principals) is computed within unit j as:

$$\bullet \ddagger k\grave{a}_{\acute{y}} o L \frac{\bullet \dagger: \quad \ddot{U} \dot{y}_{\acute{y}}}{¥ \overline{0}_{\acute{y}}}$$

and in the weighted case (teachers):

$$\bullet \ddagger k\grave{a}_{\acute{y}} o L \frac{\bullet \dagger: \quad \ddot{U} \dot{y}_{\acute{y}}}{\sqrt{\frac{: \tilde{A} S_{æ}{}^{\cdot 6}}{: \hat{A} S_{æ}^{6};}}} \acute{a}$$

where $\bullet \dagger: \quad \ddot{U} \dot{y}_{\acute{y}}$ is the sample standard deviation of the SGPs in group j and N is the number of students in group j

Through the Edwin Analytics system, educators can also obtain MGPs based on the following subgroups:

- **Students with Disabilities.** Students identified as having disabilities by the Committee on Special Education and receiving services under the Individuals with Disabilities Education Act (IDEA), based on district-provided information.
- **ELLs.** Students identified as English Language Learners, defined as students who, by reason of foreign birth or ancestry, speak a language other than English and either (1)

Results

Results From Growth Models for Grades 4–8

This section provides an overview of the results of 2013±14 growth model estimation. Some comparisons to earlier year growth model results are also included. A pseudo R-squared statistic and summary statistics characterizing the SGPs, MGPs, and their precision provide an overview of model fit. Note that this section focuses on teacher-level and school-level results, although additional information on principal-level results is available in Appendix I. The appendices to this report provide more detailed information on model behavior and results, including model coefficients and variance components.

Model Fit Statistics for Grades 4–8

The R-square is a statistic commonly used to describe the goodness-of-fit for a regression model. Because the model implemented here is a mixed model and not a least squares regression, we refer to this as a pseudo

Precision of the MGPs for Grades 4–8

The caterpillar plot in Figure 7 is a random sample of 100 teacher MGPs taken from the 2013±14 data. The MGPs are sorted from lowest to highest, with the corresponding 95 percent confidence range showing the lower and upper limits of the MGP. Figure 8 shows the same type of plot for schools (where larger underlying samples mean that there is substantially less variation in the MGP and the error bars are narrower). These figures provide a sample of the distribution of MGPs and a typical confidence range.

Figure 7. Grades 4–8 Overall MGP With 95 Percent Confidence Interval Based on Random Sample of 100 Teachers

Figure 8. Grades 4–8 Overall MGP With 95 Percent Confidence Interval Based on Random Sample of 100 Schools

Figure 11. Relationship of Grades 4–8 Teacher MGP Scores to Percentage of Economically Disadvantaged Students in Class or Course

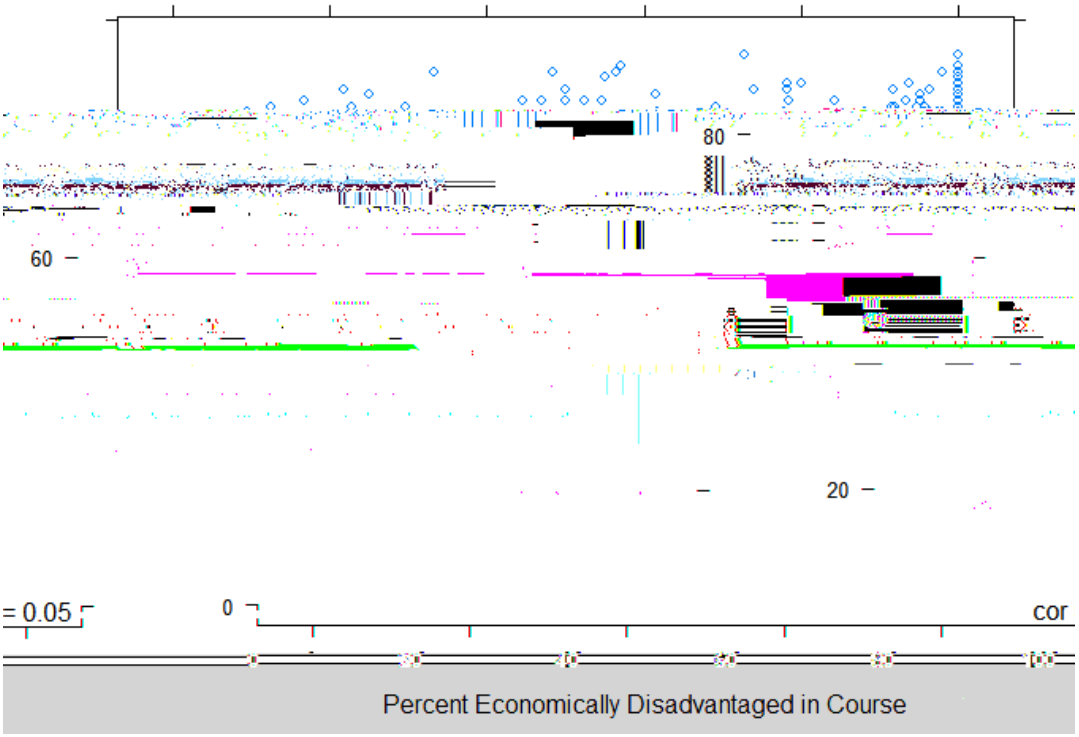


Figure 12. Relationship of Grades 4–8 Teacher MGP Scores to Mean Prior ELA Scores in Class or Course

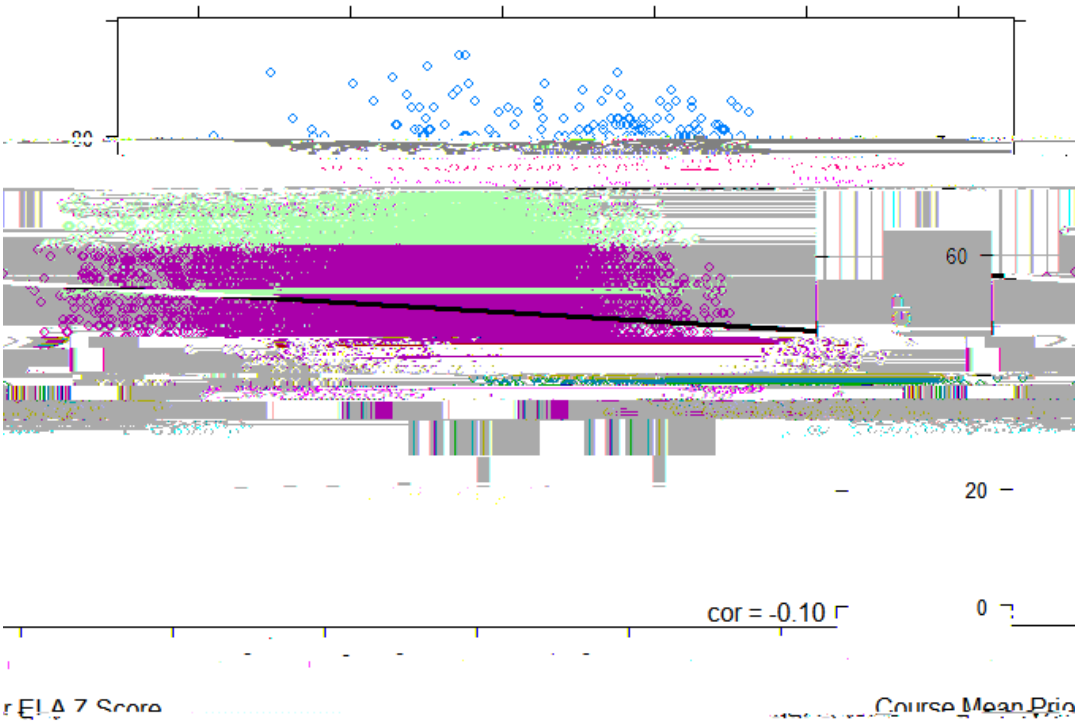


Figure 13. Relationship of Grades 4–8 Teacher MGP Scores to Mean Prior Mathematics Scores in Class or Course

Table 16 provides the observed correlations of school MGPs with the same characteristics presented for teachers, but aggregated to the school level. Correlations decreased between 2012± 13 and 2013±14, and all characteristics explain less than one-half of 1 percent of the variance in MGPs. Appendix I contains principal-level correlations.

Table 16. Grades 4–8 School MGP Correlated With School Characteristics

Percentage	2012–13 Adjusted Model	

Figure 14. Relationship of Grades 4–8 School MGP Scores to Percentage of ELL Students

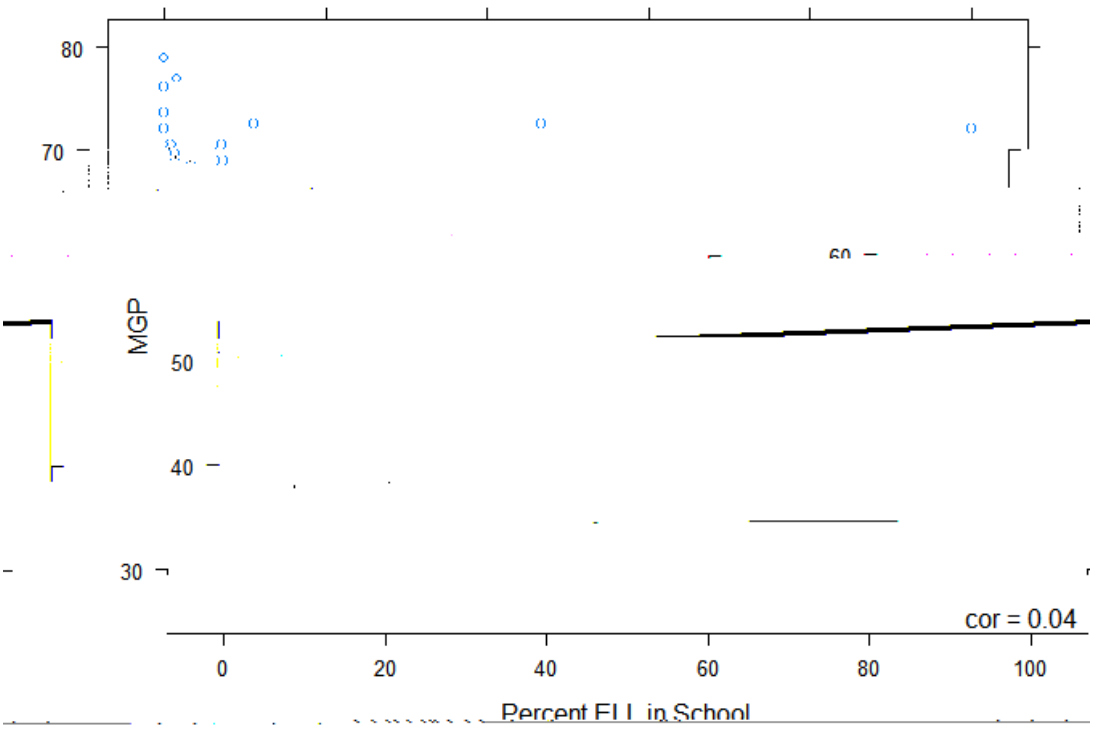


Figure 15. Relationship of Grades 4–8 School MGP Scores to Percentage of Students With Disabilities in School

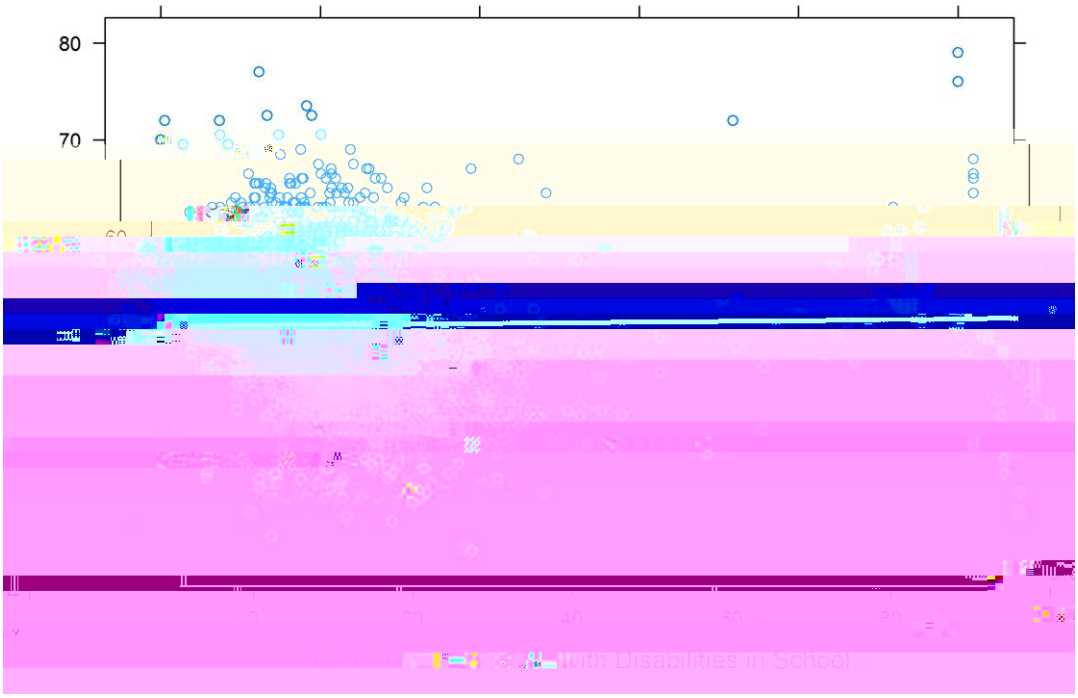


Figure 18. Relationship of Grades 4–8 School MGP Scores to Average Prior Mathematics Scores

Growth Ratings for Grades 4–8

This section describes the observed distribution of the growth ratings assigned using the rules described earlier in the results section. Table 17 shows the distribution for Grades 4±8 teachers, schools, and principals who serve students in Grades 4±8 (including, for instance, schools serving Grades 4±12) for 2011±12 to 2013±14.

Table 17. Grades 4–8 Teacher, School, and Principal Growth Ratings

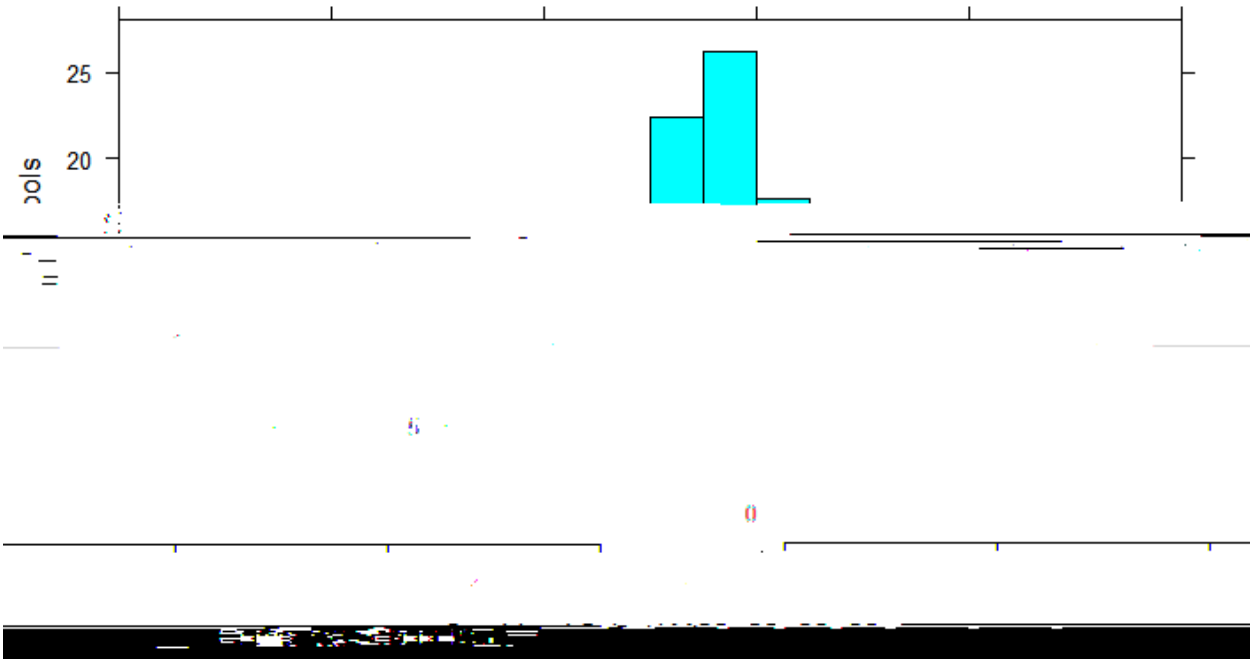
School Year	Educator Level	Highly Effective	Effective	Developing	Ineffective
2011±12	Teacher	7%	77%	10%	6%
	School	6%	79%	8%	7%
2012±13	Teacher	7%	76%	11%	6%
	School	9%	75%	9%	7%
2013±14	Teacher	8%	77%	10%	6%

Stability of Growth Ratings for Grades 4–8 Over Time

For teachers who had growth ratings in 2012±13 and 2013±14, Table 18 shows the relationship between ratings across years. Table 19 shows the relationship for school-level MGPs. The results show that the ratings are stable, with about two-thirds remaining in the same growth rating category from year to year. The MGPs have a Pearson correlation coefficient of 0.42 for teachers and a correlation coefficient of 0.38 for schools between 2012±13 and 2013±14. These correlation coefficients are larger than those often reported in the literature on growth scores (e.g., see McCaffrey, Sass, Lockwood, & Mihaly, 2009), suggesting that the New York State MGPs are relatively stable compared with other growth measures.

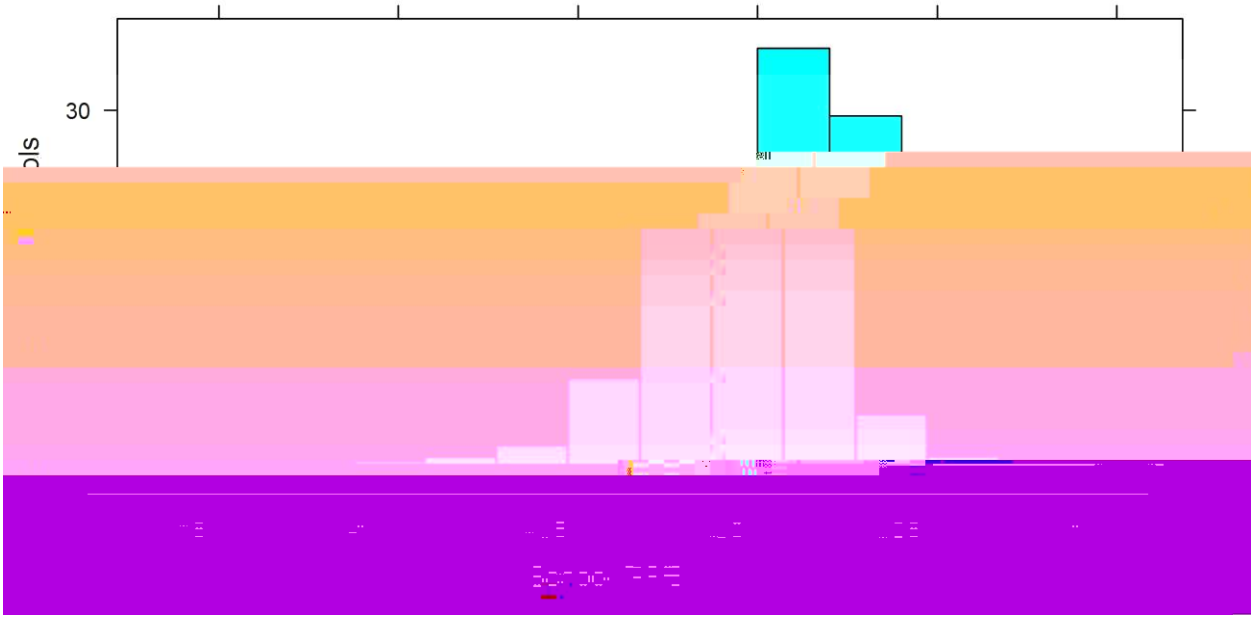
Table 18. Grades 4–8 Teacher Growth Ratings for Teachers Present in Both 2012–13 and 2013–14

Figure 19. Grades 9–12 Distribution of School MGP, Adjusted Model



The GRE model reports results as the number of Regents Exams that the average student in a school will pass compared to the number passed by similar students. For example, a GRE score of 0.25 would indicate that, on average, students in that school pass one-quarter of a Regents Exam more than do similar students. Over four years of high school, this rate per year would add up to an additional Regents Exam passed by each student. Figure 20 displays a histogram of GRE results. GRE results are somewhat skewed relative to the normal distribution.

Figure 20. Grades 9–12 Distribution of School GRE Scores, Adjusted Model



Precision of the Measures for Grades 9–12

The caterpillar plot in Figure 21 shows 100 randomly selected school MGPs and their confidence interval, giving a sense of the precision of the estimates. A second caterpillar plot in Figure 22 shows the GRE measure values and the associated confidence intervals. In both of these plots, it is apparent that the confidence intervals are small relative to the overall dispersion in the measures themselves.

Figure 21. Grades 9–12 Caterpillar Plot of School MGPs

Figure 22. Grades 9–12 Caterpillar Plot of School GRE Results

Table 22 shows the share of Grades 9±12 schools whose scores are significantly different from the mean (their confidence intervals on the caterpillar plot do not cross the average value). Once again, the share exceeds what would be expected by chance alone, indicating that the model is able to distinguish among schools.

Figures 23 through 27 plot these data for MGP results, and Figures 28 through 32 plot these data for GRE results. The higher demographic correlations for the GRE measure (as compared to the MGP measure) are not surprising, given that the GRE measure is rooted in a status (or achievement) metric: passing enough Regents exams to earn a NYS diploma. At the same time, it is important to note that there is variation in school-level results at all levels of average prior achievement (as seen in the following figures), suggesting that schools can demonstrate strong results regardless of school characteristics.

Figure 23. Relationship of Grades 9–12 School MGP Scores to Percentage of ELL Students

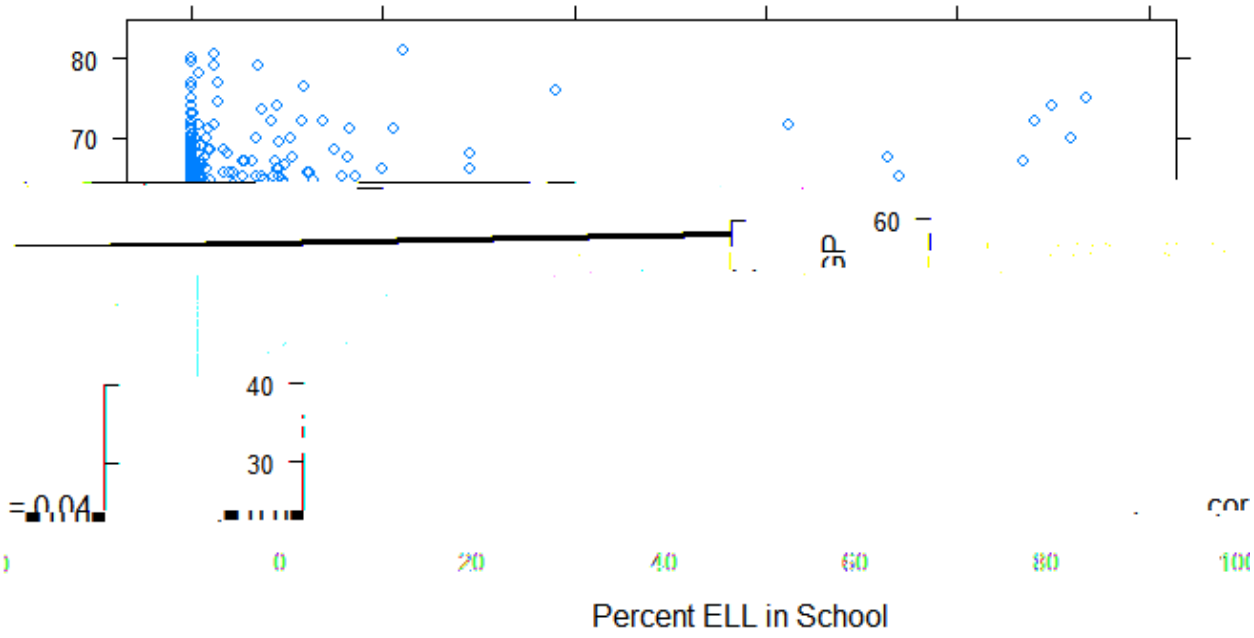


Figure 26. Relationship of Grades 9–12 School MGP Scores to Average Prior ELA Scores

Figure 27. Relationship of Grades 9–12 School MGP Scores to Average Prior Mathematics Scores

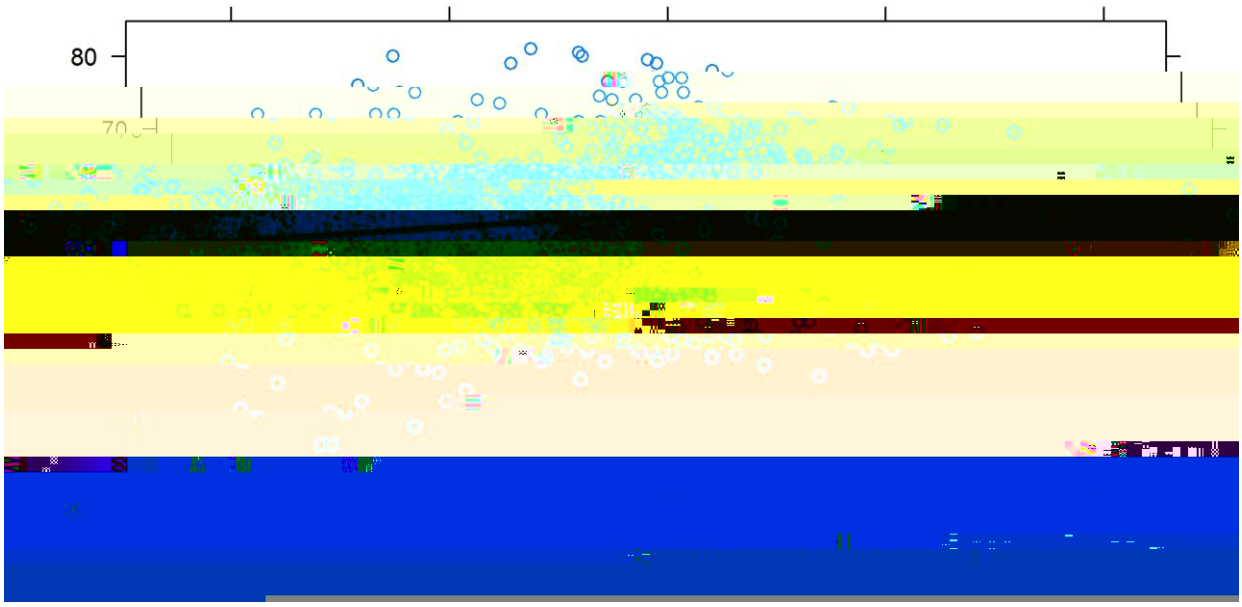


Figure 28. Relationship of Grades 9–12 School Growth in Regents Exam (GRE) Scores and Percentage of ELL Students in the School

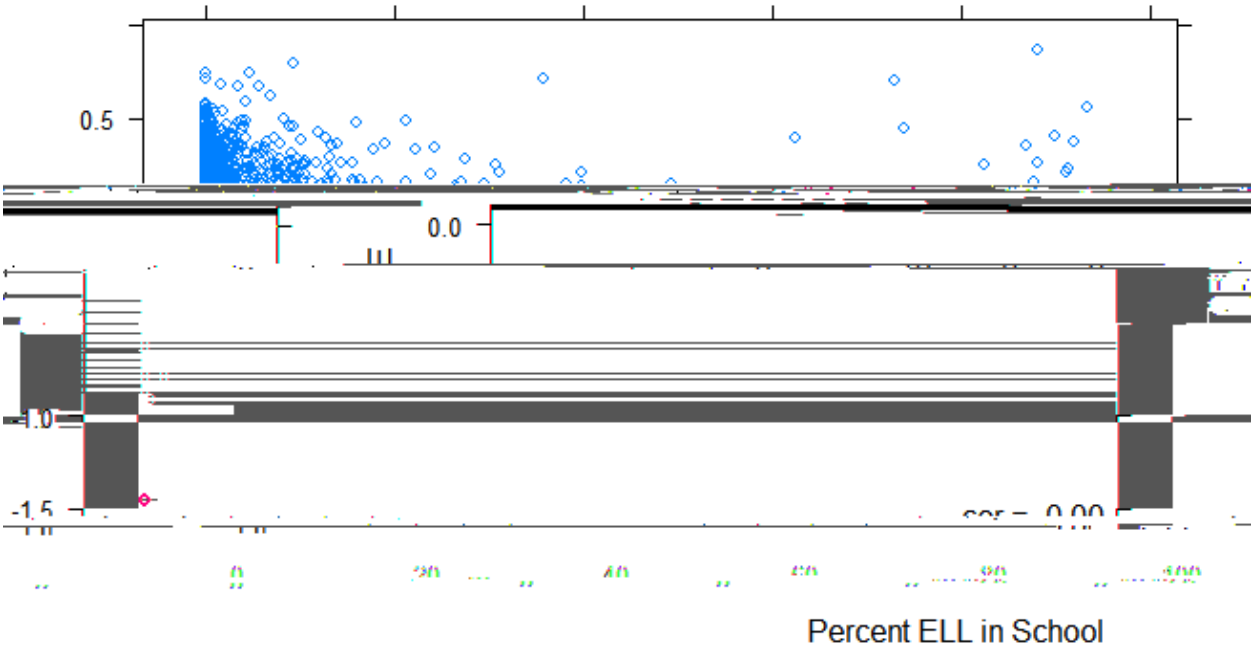


Figure 29. Relationship of Grades 9–12 School Growth in Regents Exam (GRE) Scores and Percentage of Students With Disabilities in the School

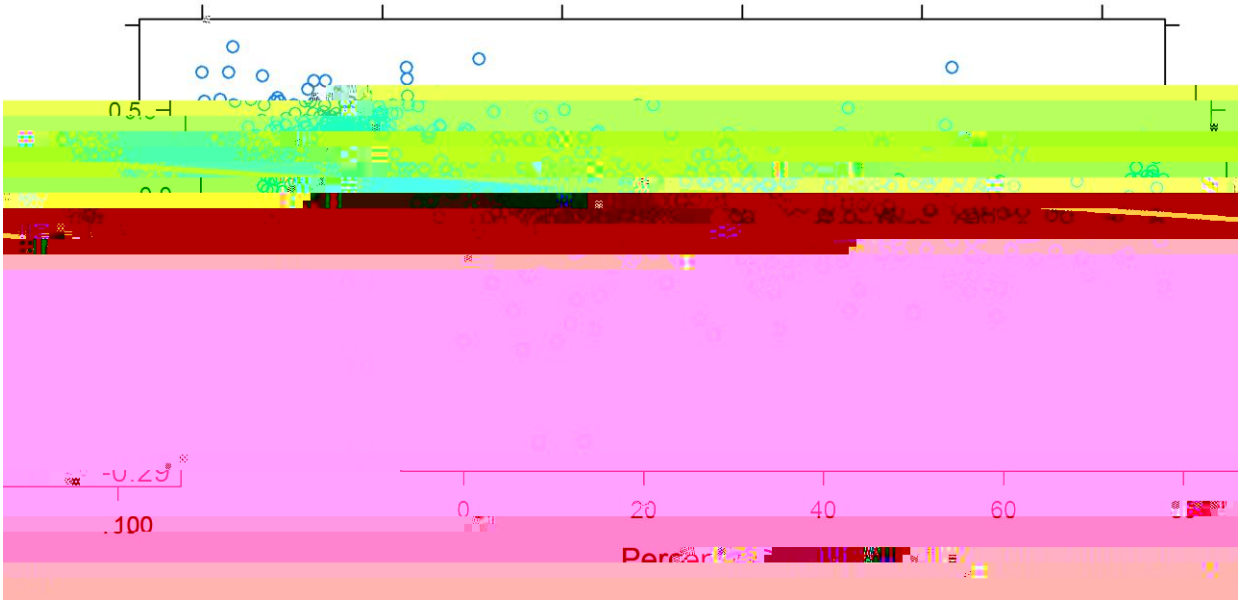


Figure 30. Relationship of Grades 9–12 School Growth in Regents Exam (GRE) Scores and Percentage of Economically Disadvantaged in the School

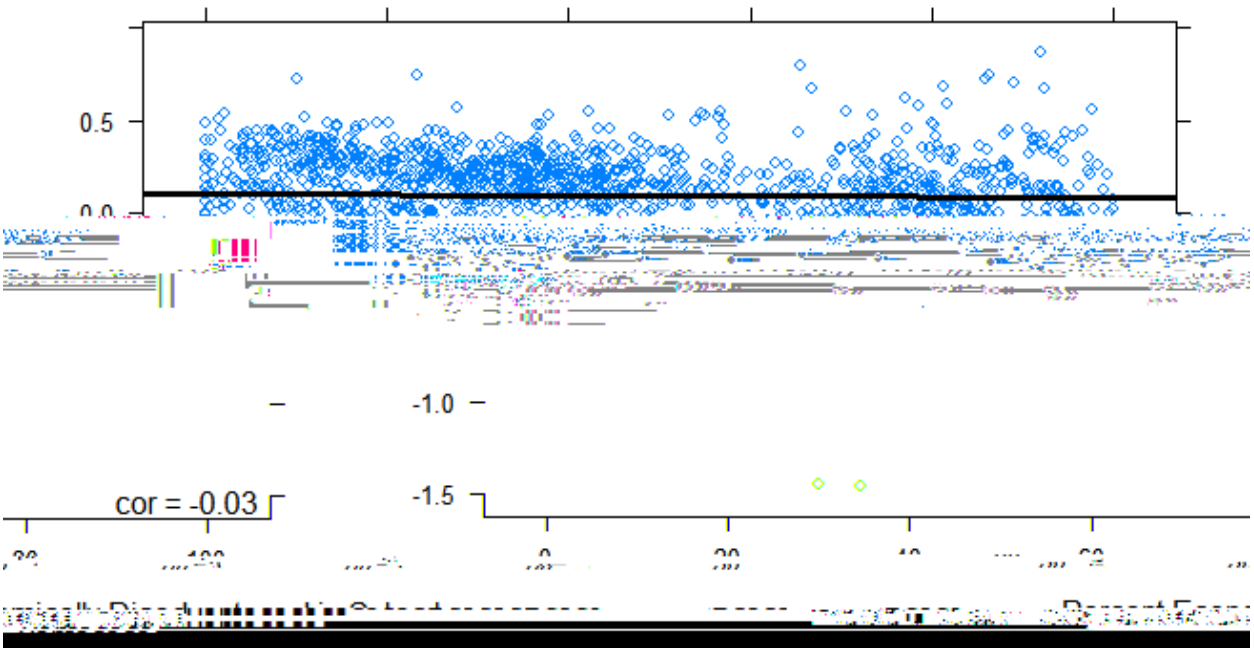


Figure 31. Relationship of Grades 9–12 School Growth in Regents Exam (GRE) Scores and Average Grade 8 ELA Scale Scores

Figure 32. Relationship of Grades 9–12 School Growth in Regents Exam (GRE) Scores and Average Grade 8 Mathematics Scale Scores

Growth Ratings for Schools of Grades 9–12

Table 25 shows the distribution of growth ratings for schools and principals of all schools serving Grades 9±12 (including schools that may also serve other grades, such as Grades 4±8). Note that principal-level ratings were not computed in 2012±13.

Table 25. Distribution of Growth Ratings for Schools and Principals of Grades 9–12 in 2012–13 and 2013–14

Year	Educator Level	Highly Effective	Effective	Developing	Ineffective
2012±13	School	2%	86%	11%	2%
2013±14	Principal	3%	82%	12%	3%
	School	3%	82%	12%	4%

Note:

Table 26 shows the relationship between school ratings across years. The results show that the ratings are stable, with about 84 percent of schools remaining in the same growth rating category from year to year.

Table 26. Grades 9

Conclusion

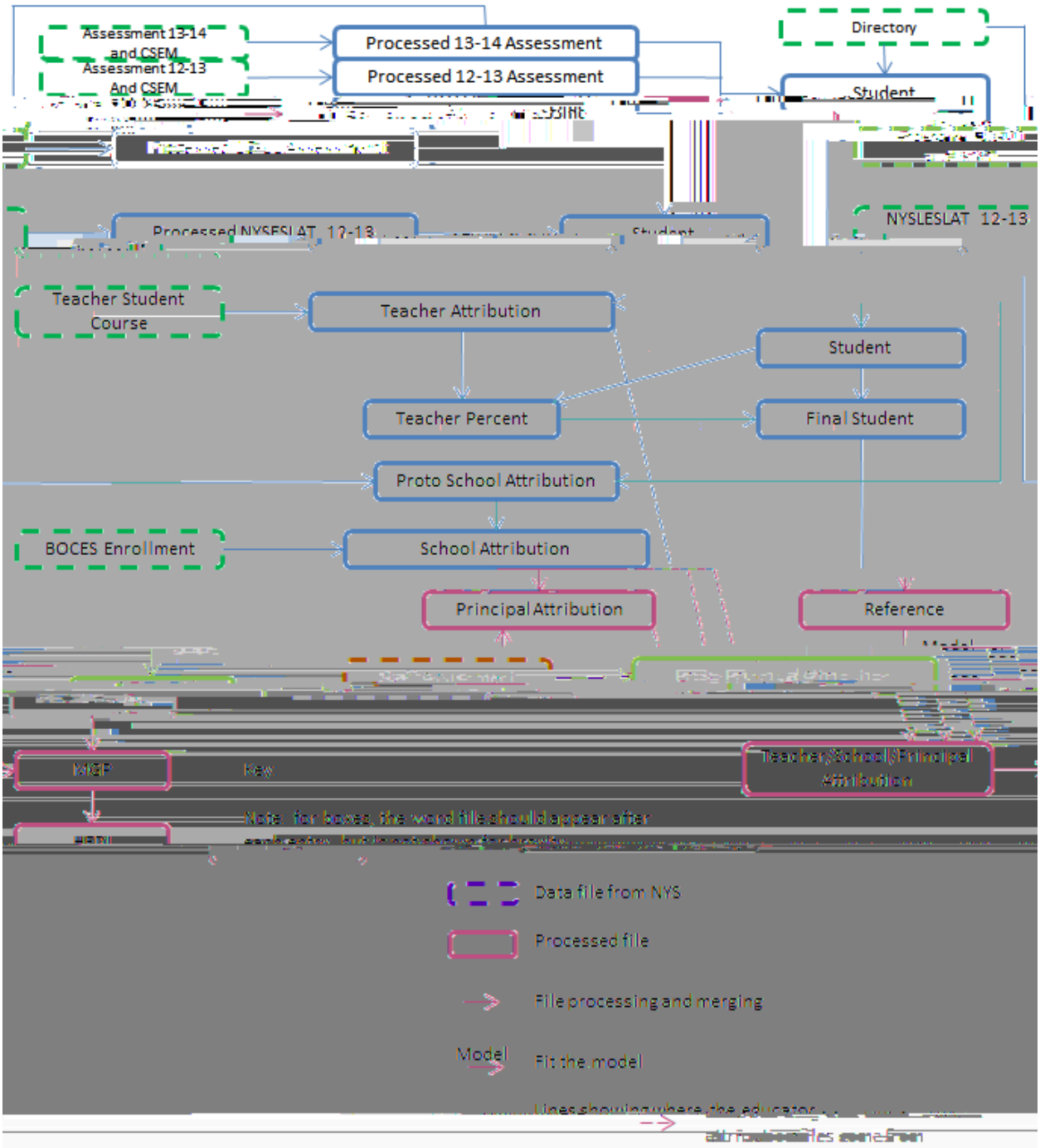
In 2014±15, New York State plans to maintain the MGP and GRE models used to produce educator growth measures, including the student characteristics accounted for in the models, while continuing to provide technical support to the field in the areas of data collection and reporting.

Appendix A. Technical Advisory Committee Members

Participant	Affiliation*
Technical Advisory Committee	
Dan Goldhaber	University of Washington
Hamilton Lankford	State University of New York at Albany
Daniel F. McCaffrey	Educational Testing Service/RAND
Jonah Rockoff	Columbia University
Tim R. Sass	Georgia State University
Douglas Staiger	Dartmouth College
Marty West	Harvard University
James A. Wyckoff	University of Virginia

1RWHWKDWDIILOLDWLRQVDUHYDOLGIRUWKHSHULRGIURP7HFKQLFDO6XEPLVVLRQ*URXS0HHWLQJWKURXJK
2012 and 2013.

Appendix B. Grades 4–8 Data Processing Overview



Appendix D. Model Derivation

The following describes a general case of the

where $\dot{U}_{\perp}$ is a matrix of dimension of L with elements of 0, and

$$\bullet_{\text{Å}} L f \begin{matrix} Q_{\text{ß}5} & Q_{\text{ß}6} & \text{å} & Q_{\text{ß}\text{Å}} \\ Q_{\text{ß}5} & Q_{\text{ß}6} & \text{å} & Q_{\text{ß}\text{Å}} \\ - & - & \circ & - \\ Q_{\text{ç}5} & Q_{\text{ç}6} & \text{å} & Q_{\text{ç}\text{Å}} \end{matrix} j$$

The theoretical result of the matrix operation yields the following symmetric matrix:

$$P^{\tilde{n}.\ ?5}\ {}_{P}L \begin{matrix} \text{í} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q^{6}_{\text{ú}5} & & \text{å} & \text{Þ} \\ \text{î} & & & & \tilde{N} \\ \text{î} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q_{\text{ú}5}Q_{\text{ú}6} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q^{6}_{\text{ú}6} & \text{å} & \tilde{N} \\ \text{î} & - & - & \circ & \tilde{N} \\ \text{Î} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q_{\text{ú}5}Q_{\dot{U}\text{Å}} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q_{\text{ú}6}Q_{\dot{U}\text{Å}} & \text{å} & \tilde{A}_{\text{Ç}\dot{U}@5} \frac{5}{\text{ß}\hat{O}} Q^{6}_{\dot{U}\text{Å}} & \tilde{N} \\ \text{ï} & & & & & \text{Õ} \end{matrix}$$

The theoretical result is limited only because we do not observe $Q_{\dot{U}\text{á}}$ because it is latent. However, $'\ kQ_{\dot{U}\text{á}}Q_{\dot{U}\text{á}}oL\ \hat{e}^{6}_{\dot{U},\tilde{a}}$ where $\hat{e}^{6}_{\dot{U}\text{á}}$ is taken as the conditional standard error of measurement for student i. The theoretical result also simplifies because variances of measurement on different variables are by expectation uncorrelated: $'\ kQ_{\dot{U}\text{á}}Q_{\dot{U}\tilde{a}}oL\ r$ when $L\ M\ L$."

Because the conditional standard error of measurement varies for each student i and the off-diagonals can

Appendix E. Interpolating Standard Errors of Measurement at the Lowest and Highest Obtainable Scale Scores (LOSS and HOSS)

The linear model used to produce student-level predictions $\hat{Y}$ can cause these predictions to fall outside the boundaries of the defined score scale. Let the floor and ceiling in the data be denoted as A_C and A_D respectively. It is therefore possible that $\hat{Y} < A_C$ or $A_D < \hat{Y}$. However, the observed score can never fall outside these bounds.

When a prediction falls outside the boundaries of the score scale, it can cause bias in the statistics used to characterize a student, teacher, or school. This phenomenon seems to occur as a result of the large conditional standard errors of measurement at the extreme scores, $\sigma(\hat{\theta})$. The following procedure is implemented to deal with these large standard errors.

Interpolation Procedure for Conditional Standard Errors of LOSS and HOSS

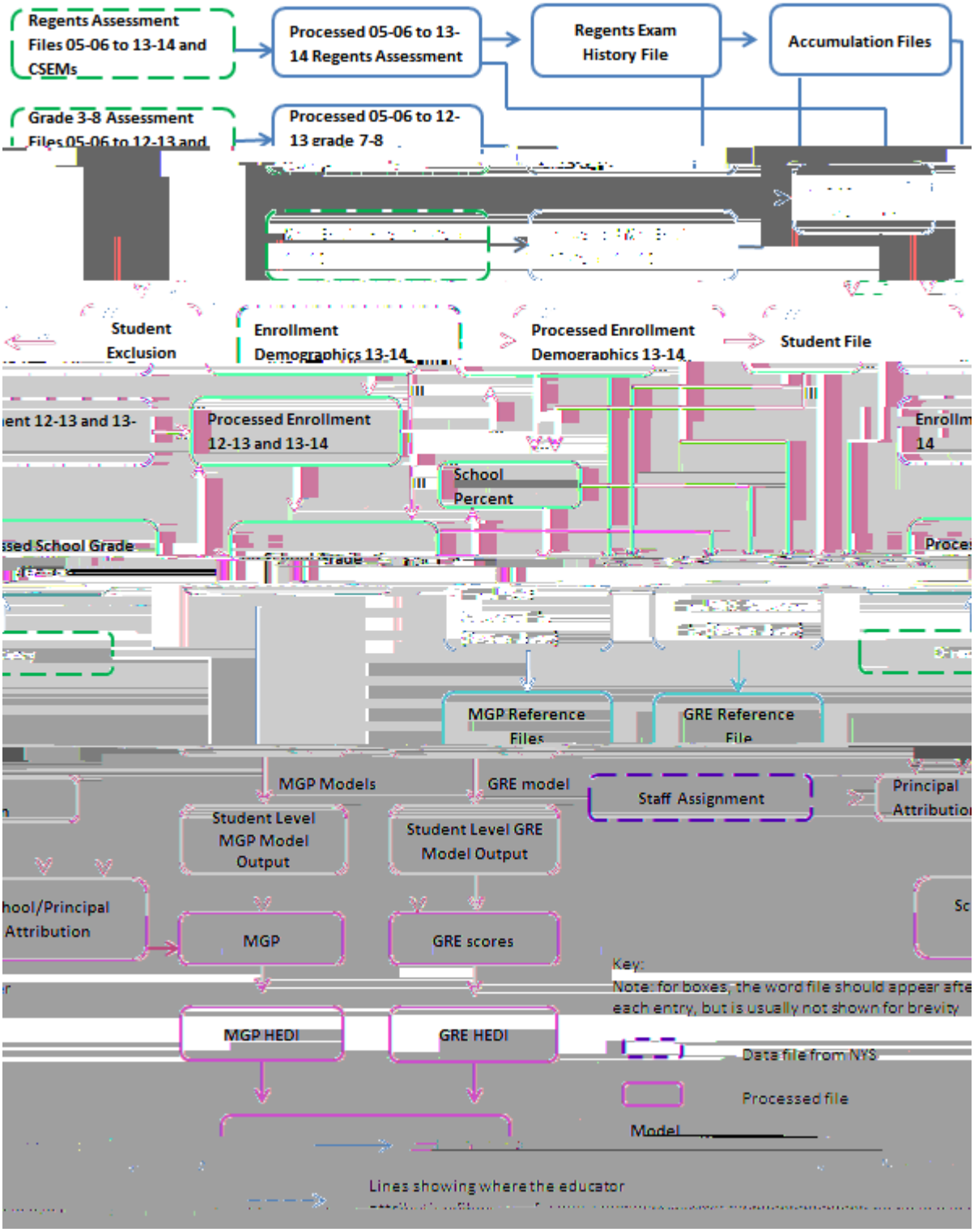
Interpolate new conditional standard errors of measurement as the 3 nearest neighbor´ or any extreme value. Thus, for an $M = 2$ cutoff, the HOSS and score immediately below the HOSS, the SEM associated with the score two below the HOSS would be used. Similarly, the LOSS and score immediately above the LOSS would have the SEM associated with the score two above the LOSS. As M increases, more points are included, and the point they are set to moves in toward the middle of the scale score distribution.

Implement the linear regression using the following steps:

1. Run the regression without modification.
2. Verify that $D_d < \hat{Y}_g < D_a$ for all i.
3. If the inequality in step 2 is true, stop; the run is complete. Otherwise, continue to step 4.
4. Set $M = 1$ and update the SEMs of the exact HOSS and LOSS scores.
5. Use the updated $\sigma(\hat{\theta}_g)$ in lieu of the standard error of the LOSS or HOSS in the test score data.
6. Run the growth model.
7. Verify the inequality in step 2; if it holds, stop updating. If it does not hold, increase M by 1 and return to step 5.

If this method does not result in the inequality in step 2 being met after $M = 7$ (i.e., after running with $M = 7$), then simply take the most recent run that did converge, set $\hat{Y}_g = D_a$ where $\hat{Y}_g > D_a$ and $\hat{Y}_g = D_d$ where $\hat{Y}_g < D_d$. For the predicted variance, use the predicted variance of the closest estimate where the inequality in step 6 does hold.

Appendix F. Grades 9–12 Data Processing Overview



Appendix G. Assigning HEDI Ratings and Points

HEDI ratings are assigned according to Figure G-1, shown in the body of the report but repeated here for reference.

Figure G-1. HEDI Rating Rules

HEDI ratings are assigned in Grades 4±8 for the combined MGPs (pooled across Grades 4±8 ELA and Grades 4±8 mathematics), in Grades 9±12 for the combined growth model (pooled across ELA and Algebra), and in Grades 9±12 for the GRE model. Values used in 2013±14 to assign HEDI ratings for teachers are shown in Table G-1; for schools, in Table G-2; and for principals, in Table G-3.

Table G-1. Teacher HEDI Rating Values for 2013–14

Mean	51.0907
SD	10.80857
Highly Effective	**0*3DQFRQGHQHUDQHORZHUOLPLW!**
Effective	**0*3DQFRQGHQHUDQHORZHUOLPLW”**
Effective	40 < MGP < 67
Effective	**0*3fwQ€**

Table G-2. School HEDI Rating Values for 2013–14

	Grades 4–8 Growth Model	Grades 9–12 Growth Model	Grades 9–12 GRE Model
Mean	50.87795	55.86970	0.096244
SD	6.225419	7.961927	0.236486
Highly Effective	**0*3DQ** confidence range lower limit > 51	**0*3DQ** confidence range lower limit > 56	**"5(DQ** confidence range lower limit > 0.10
Effective	**0*3DQ** confidence range lower **OLPLW"**	**0*3DQ** confidence range lower **OLPLW"**	**"5(DQ** confidence range lower **OLPLW"**
Effective	45 < MGP < 60	48 < MGP < 68	-0.14 < GRE < 0.45
Effective	42 < MGP **ĐQ** confidence range upper **OLPLW•**	**0*3ĐQ** confidence range upper **OLPLW•**	

Table G-6. Grades 4–8 School HEDI Point Distribution

	HEDI Score Points		HEDI Score Points in NYC	
HEDI Points	**Min MGP**	**Max MGP**	**Min MGP**	**Max MGP**
0	27.5	38.0	27.5	33.5
1	38.5	40.0	34	35.5
2	40.5	42.0	36	36.5
3	31.5	42.0	37	37.5
4	42.5	42.5	38	38
			38.5	38.5

Table G-7. Grades 4–8 Principal HEDI Point Distribution

	HEDI Score Points		HEDI Score Points in NYC	
HEDI Points	**Min MGP**	**Max MGP**	**Min MGP**	**Max MGP**
0	27.5	38	27.5	33.5
1	38.5	40	34	35.5
2				

1. Find the aggregate HEDI growth score using the following equation:

$$) \; L \frac{J_{\circ}) \circ \; E \; J_{\raisebox{0.5ex}{\scriptsize »}}) \raisebox{0.5ex}{\scriptsize »}}{J_{\raisebox{0.5ex}{\scriptsize »}} \; E \; J_{\raisebox{0.5ex}{\scriptsize »}}} \; á$$

   where G is the growth score, n is the number of students attributed to a school, the subscript A is used to indicate one of the two HEDI scores being combined, and the subscript B is used to indicate the other. If either of the HEDIs is not assigned because the n was not at least 16, simply set G equal to the assigned HEDI score and continue. For example, if only $J_{\circ}$ is greater than or equal to 16 ($J_{\circ}$ R s xá$J_{\raisebox{0.5ex}{\scriptsize »}}$ O s x, then:) L)◦.

   The same also holds if A and B are switched in the example. Also, if neither HEDI was assigned ($J_{\circ}$ O s xá$J_{\raisebox{0.5ex}{\scriptsize »}}$ O s x, set G to missing and not included in the final HEDI score.

2. Round G to the nearest integer. This integer is the HEDI score for the combination.

3. For all principals and schools, assign a final HEDI rating by using the cut points table, DVVLJQLQJWKH+(',UDWLQJDVVRFLDWHGZLWKHDFKVFKRROORUSULQFLSDO¶VILQDOUH points value (G from step 2 above) based on the column labeled ³+(',6FRUH 3RLQWV´

4. Every principal and school with two HEDI ratings and scores to combine is assigned a New York City HEDI rating and score by applying the rules for assigning scores described above to the unrounded value of G found in step 1. NYC ratings are then reported only to educators in NYC.

Appendix H. Model Coefficients

7KHWDEOHVWKWIROORZGLVSODUHJUHVVLRQRGHOFRHIILFLHQVODEHOHGDV?IIHFWV
York growth models in each grade and subject. For the Grades 4-8 models and Grades 9-12
MGP models, these model coefficients represent the p(se)39na 5T[dh c(a)4(n)-9(he)4(in2)] TJETBT1 0 0 14522

csentty ea(tes sco)-seg a

untith(a)4(n)-9(g)10hem2 -eachvh(a)4ria55obie shrow(in2it)-3hdetableegthet.
(a)4mpliH -

Table H-3. Grade 5 ELA Model Coefficients, Unadjusted Model

Effect Name	Effect	Standard Error	p-value
Constant Term	±158.973	2.754	0.000

Table H-9. Grade 8 ELA Model Coefficients, Unadjusted Model

Effect Name	Effect	Standard Error	p-value
Constant Term	±283.828	4.309	0.000
Prior-Grade ELA Scale Score	0.705	0.004	0.000
Two-Grades-Prior ELA Scale Score	0.427	0.009	0.000
Missing Flag: Two-Grades-Prior ELA Scale Score	281.015	5.695	0.000
Three-Grades-Prior ELA Scale Score	0.132	0.006	0.000
Missing Flag: Three-Grades-Prior ELA Scale Score	88.862	3.761	0.000

Table H-10. Grade 8 ELA Model Coefficients, Adjusted Model 0.000

Effect Name	Effect	Standard Error	p-value
Constant Term	±451.877	10.058	0.000
Prior-Grade ELA Scale Score	0.608	0.004	0.000
Grades-Prior ELA Scale Score	0.412	0.009	0.000
ng Flag: Two-Grades-Prior ELA Scale Score	270.253	5.730	0.000
-Grades-Prior ELA Scale Score	0.110	0.006	0.000
ng Flag: Three-Grades-Prior ELA Scale Score	75.393	3.728	0.000
Grade Mathematics Scale Score	0.114	0.003	0.000
ng Flag: Prior-Grade Mathematics Scale Score	30.167	1.043	0.000
Prior Score	0.059	0.004	0.000
e Around Prior Score			

Table H-11. Grade 4 Mathematics Model Coefficients, Unadjusted Model

Effect Name	Effect	Standard Error	p-value
Constant Term	±0.878	0.525	0.095
Prior-Grade Mathematics Scale Score	1.016	0.002	0.000

Table H-12. Grade 4 Mathematics Model Coefficients, Adjusted Model

Effect Name	Effect	Standard

Table H-21. Grades 9–12, Algebra Model Coefficients, Unadjusted Model

Effect Name	

Effect Name	Estimate	Standard Error
Missing Flag: Mean Prior Grade 8 ELA 2012±13	14.870	

Table H-31. Grades 9–

Table H-33. Grades 9–12, GRE, Year in School 3 Model Coefficients, Unadjusted Model

Effect Name	Estimate	Standard Error
Intercept 1	±10.336	0.143
Intercept 2	±11.461	0.144
Intercept 3	±13.449	0.145
Intercept 4	±15.791	0.146
Intercept 5	±18.130	0.150
Intercept 6	±20.691	0.205
Intercept 7	±22.165	0.335
Intercept 8	±24.563	1.010
Grade 8 ELA Scale Score 2011±12 and Prior		

Effect Name	Estimate	Standard Error
Missing Flag: Grade 7 Mathematics		

Table H-37. Grades 9–12, GRE, Year in School 5+ Model Coefficients, Unadjusted Model

Effect Name	Estimate	Standard Error
Intercept 1	±7.144	0.469
Intercept 2		

Appendix I. Additional Impact Correlation Tables (Grades 4–8 by Grade and Subject and Grades 4–8 and 9–12 Principal)

Table I-1. Impact Correlations by Grade for ELA

Grade	Percent ELL	Percent Students With Disabilities	Percent Economically Disadvantaged	Mean Prior Scale Score
4	0.04	0.10	0.06	0.03
5	0.08	0.04	0.06	0.08
6	0.03	0.07	0.03	±0.01
7	0.12	0.06	0.10	±0.02
8	0.08	0.06	0.03	0.00