NYC Teacher Data Initiative:
Technical Report on the NYC Value-Added Model
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INTRODUCTION

Conceptually, value-added analysis is the use of statistical technique to isolate the component of measured student knowledge that is attributable to schools, teachers, or classrooms from other factors such as prior knowledge, student and classroom characteristics, and other factors using the available data. In practice, value-added models focus on the improvement students make on annual assessments from one year to the next. Value-added models often control for measurable student characteristics such as race, income, and disability, and measurable classroom characteristics such as class size to help isolate the impact of schooling. The model in New York City uses a large set of student and classroom characteristics to identify the extent to which teachers contribute to the improvement of student achievement outcomes in their classrooms.

This technical report describes the value-added model used by the NYC Department of Education and developed in association with the Value-Added Research Center of the Wisconsin Center for Education Research at the University of Wisconsin. The report is in four parts. The first part describes the data set used to produce the value-added estimates. The second part describes the model used to estimate value added for teachers in New York. The third part describes the reporting of value added. Finally, the fourth part presents the results of analyses of the properties of the value-added results.

ANALYSIS DATA SET

Before estimation can take place, a substantial amount of work is required to assemble the analysis data sets used to produce the value-added estimates. A separate analysis data set is produced for each grade, subject, and year. In total, forty analysis data sets are produced, covering five grades (fourth, fifth, sixth, seventh, and eighth), four years (2005-06, 2006-07, 2007-08, 2008-09), and two subjects (mathematics and English Language Arts). The analysis data sets include students with a posttest and pretest in consecutive grades in the same subject who could be assigned to a school, classroom, and teacher for that subject.

The analysis data set onwhich the value-added model is run includes both student-level and classroom-level variables. Variables at the student level provide information about individual students, while variables at the classroom level provide information about the classrooms students are in (including the average characteristics of the students in the classroom).

Student-level variables

Posttest and pretest variables

The test scores used in the data set are scores from the New York State test examinations in mathematics and English Language Arts for students in grades three through eight in 2005, 2006, 2007, 2008, and 2009. In 2005, the New York State test examination was given to fourth and eighth grades only; New York City administered assessments to students in third, fifth, sixth, and seventh grade. The city assessments were used in place of the state exams for these grades in 2005.

For the value-added analysis, scale scores were converted into z-scores, which have a mean of 0 and a standard deviation of 1 across the city. Scale scores in math and ELA are normalized within grade and year into z-scores by subtracting from scale scores the within-subject, within-grade, within-year mean and dividing that result by the within-subject, within-grade, within-year standard deviation. The normalization takes place across all students in the city with test scores. After z-scores are computed, duplicate observations are handled by dropping all observations with duplicate student IDs except that with the highest z-score.

Standard errors of measurement of pretest variables

The standard errors of measurement (SEM) of math and ELA z-scores are set to 1 minus the square root of Cronbach's alpha in most years, grades, and subjects. Cronbach's alpha is available in the technical reports of the New York State and City assessments. Exceptions are fourth and eighth grade in 2005, which replaces Cronbach's alpha with a Feldt-Raju measure of reliability, and for the other grades in ELA in 2005, which replaces Cronbach's alpha with a Kuder-Richardson reliability measure. Given the use of an unconditional measurement error measure, every student in the same year and grade has the same SEM for a given test. The standard errors of measurement are used for a correction for measurement error in the pretest. It is presumed that the covariance between the measurement errors of math and ELA pretests is zero.

Imputation of missing other-subject pretest scores

Some students have scores for posttest and same-subject pretest but not for other-subject pretest. This is very rare in ELA, but it is less rare in mathematics; these are cases in which students have a math posttest and math pretest but no ELA pretest.[1] To avoid throwing out cases where same-subject posttest and pretest is available but other-subject pretest is missing, other-subject pretest is imputed for cases where same-subject pretest is available. This is accomplished by running a regression of other-subject pretest on same-subject pretest, a vector of student-level variables, and a complete set of classroom dummy variables over observations for which same-subject pretest is available. The regression makes a correction for measurement error in same-subject pretest based on the same-subject pretest's SEM to ensure that the regression coefficients were estimated properly. The coefficients from this regression equation are used to impute a predicted other-subject pretest using same-subject pretest, student-level variables, and classroom for cases where other-subject pretest is missing. If a student with a missing other-subject pretest is in a classroom not represented in the data set used for the imputation regression--which is the case when no students in the classroom took the other-subject pretest--the average classroom effect is used instead.

[1] As of 2007, the New York State Education Department updated its testing policy for English Language Learners. ELLs who have attended school in the US for more than one year must take the ELA exam. Previously, ELLs who had attended school in the US for less than four years were exempt from taking the ELA exam.

The standard error of measurement (SEM) for imputed other-subject pretests is set to the product of the SEM of the same-subject pretest and the coefficient on same-subject pretest in the imputation regression. This is the standard error of the component of the imputed other-subject pretest that is predicted with the same-subject pretest. Because the same-subject pretest is used in the imputation, there is also a covariance between the measurement error of the same-subject pretest and imputed other-subject pretest. Since these measurement errors are perfectly correlated, this covariance is equal to the product of the SEMs of the same-subject pretest and the imputed other-subject pretest.

Gender, race, and free- and reduced-price lunch

Gender, race, and free- and reduced-price lunch are drawn from the student biographical dataset. In the analysis data set, students are assigned the gender, race, and low-income status reported in the posttest year. Gender categories are male and female. Race categories are Asian, black, Hispanic, Native American, white, and other. The "other" category includes multiracial persons, students (or their parents) who refuse to answer the race question, and people who identify their race as other. Separate categories exist in the analysis data set for free lunch and reduced-price lunch.

English language learner

Two variables indicating English language learner are included in the data set: one that identifies students as current English language learners and another that identifies students as former English language learners. Students are identified as former English language learners using test data from the New York State English as a Second Language Test (NYSESLAT): students who passed the NYSESLAT in the pretest year are identified as former English Language Learners. Students are identified as current English language learners using data from the student biographical dataset for the posttest year. If students are listed both as current English language learners in the student biographical data and former English language learners in the NYSESLAT data, they are listed in the analysis data set as current English language learners.

Disability

Students are identified as having disabilities using data about special education program recommendations in the pretest year. Disability status from the pretest year is used because of the potential endogeneity of disability status from the posttest year. Endogeneity happens when two or more variables have causal effects on each other, making it difficult to determine the causal relationship when a correlation is observed. In the case of disabilities, students may improve at a faster or slower rate as a result of their disabilities, but teachers that foster faster or slower student growth may also affect their students' disability status. Students with disabilities are put into four categories based on their recommended services: related services, self-contained classroom, special education teacher support, and team teaching.

Summer school enrollment

A binary variable indicating whether a student enrolled in summer school between the pretest year and the posttest year is included in the data set. This variable is drawn from records on summer school attendance. For a student to be identified as enrolled in summer school it is insufficient for a student to be merely eligible for summer school; rather, it must be the case that he or she actually enrolled in summer school.

Absences and suspensions

The analysis data set also includes variables indicating the extent of absences and suspensions for the student. These variables are drawn from the student biographical data set in the pretest year. The pretest year is chosen to avoid endogeneity; students who are absent or suspended more often may grow more slowly regardless of who their teacher is, but particularly effective teachers may also cause their students to be less frequently absent or suspended. The absences variable is equal to the log of days absent if the student was absent for at least one day; it equals zero otherwise. The suspensions variable is equal to the log of days suspended if the student was suspended for at least one day; it equals zero otherwise. In both cases, the log is used to keep outliers with many absences or suspensions from being too influential.

Retained in grade

An indicator variable that indicates whether a student was retained in grade between the year before the pretest year and the pretest year is included in the analysis data set. This was drawn from the grade level variable in the student biographical files for the pretest and pre-pretest years. A student is considered to have been retained if he is in the same grade or lower in the later year. The indicator variable is not activated if the student was not in the NYCDOE in the pre-pretest year. This can be viewed as an assumption that students who were new to the city in the pretest year were not retained from the previous year, although this assumption is not actually necessary; the variable indicating new to city in pretest year (described later) should also pick up the average retention effect among students not in the city in the pre-pretest year.

Same school

The analysis data set includes a variable that indicates whether a student was in the same school in the pretest year as in the posttest year. School assignment is from the student-teacher-link data file. If a student does not have a school assignment in either the posttest or pretest year, the indicator variable is not activated.

New to city starting in pretest year

Students who were new to the city starting in the pretest year are identified with an indicator variable. Students are considered new to the city if student biographical data is missing for the year before the pretest year. This indicator not only serves as a control for the effect of being relatively new to the city, but also as a control for missing data for the retained in grade variable.

Classroom-level variables

Classroom means of variables in the student-level model

The student-level variables--including the pretests, though not including the posttests or the standard errors of measurement of the pretests--are averaged by classroom attended in the posttest year. The average pretest scores by classroom only include students for whom pretest scores are available. It does not include students for whom data is missing, nor does it include (in the case of other-subject pretest) students for whom pretest is imputed. An exception is made for cases in which all students in a classroom have other-subject pretest scores that are imputed. In these cases, the average of the imputed scores is used as the average other-subject pretest score of the classroom.

The average of the non-pretest student-level variables by classroom includes all of the students in the classroom, even those for whom data are missing. This is because the purpose of including classroom-level variables in the model is to account for the effects of classroom characteristics on student performance. Since students not in the analysis data set are still part of the classrooms and can influence the performance of their peers, they are included in the averages when possible. When data are missing, the variable with missing data is set to zero. This is not relevant for student-level variables drawn from data from the posttest year, since it is only in extremely rare cases that students with a classroom assignment for the posttest year also have missing biographical data for the posttest year. It is relevant for student-level variables drawn from the pretest year, since there are some cases of students with a classroom assignment for the posttest year who are missing data from the pretest year. In particular, students who are new to the city in the posttest year are missing data from the pretest year. For these cases, a variable indicating students who are new to the city in the posttest year is added to the set of variables averaged to the classroom level to ensure that missing data is not misrepresented.

When the value-added model is run, some variables that are included as student-level variables are not included in the model as classroom averages. These are cases of variables for relatively infrequent student characteristics for which a precise student-level effect with a reasonably small standard error can be measured but only an imprecise classroom-level effect with a large standard error can be measured. For example, while suspensions of individual students are included in the model, the classroom average number of suspensions is not. In practice, this means that while the effects of suspension on the individual students being suspended is controlled for in the model, the effects of being in a classroom with frequently suspended students on a student's achievement--regardless of whether they themselves were suspended or not--is not controlled for. This is not because the latter necessarily has no effect; it is simply because suspensions are sufficiently rare that there was not enough data to measure the effect precisely. Other classroom averages not included in the model are percent Native American and percent other race (which are implicitly combined with percent Hispanic, the omitted in the analysis). The classroom averages for students with disabilities who receive related services and students with disabilities who receive special education teacher support are combined into a single variable, reducing the number of disability categories at the classroom level from four to three.

New to city in posttest year

The proportion of students in a classroom new to the city in the posttest year is included as a classroom-level variable in the analysis data set. This variable serves two functions. First, it is there to control for the effect on a student's improvement of having many students in one's classroom who are new to NYCDOE starting in the posttest year, regardless of whether the student himself is new or not. Second, it is there to account for students in the classroom for whom biographical data from the pretest year are missing.

New to city in the posttest year is not included among the student-level variables because students must have both posttest and pretest scores to be in the analysis data set. Consequently, all of them have been in New York City for at least one year.

Class size

Class size is another classroom-level variable included in the model. Class size is measured by counting the number of students assigned to a classroom in the posttest year. This includes students who have missing data for other variables; all that is required for a student to count toward the count of students in a classroom is classroom assignment itself.

To minimize the influence of outliers on the analysis, class size is restricted so that it is between 6 and 45. All classrooms that have fewer than 6 students in them in the data are bottom coded to have 6 students in them; all classrooms that appear to have more than 45 students in them are top coded to have 45 students in them. It is likely that some of these cases are cases of very large or small classrooms, while others may be cases in which student-teacher-course assignment data are incomplete. Indicator variables for class size top coded (i.e., more than 45 students assigned to classroom) and class size bottom coded (i.e., fewer than 6 students assigned to classroom) were added to the data set to identify those cases. In the analyses themselves, only class size bottom coded was included as an explanatory variable, to measure any special impact of very small classrooms. Top-coded classrooms were sufficiently rare that it was not possible to produce a precisely measured effect that was special to very large classrooms.

Teacher, classroom and school

Student-teacher-classroom-school link

Students were assigned to teachers and to schools using a student-teacher link data set provided by DOE. The data set linked each student to a math classroom and to an ELA classroom, linked each math classroom to a math teacher, and linked each ELA classroom to an ELA teacher. As a result, classroom is nested within teacher. Schools are given the opportunity to verify these data annually. There are several cases in which two team-teaching teachers are linked to a classroom. When this took place, the two teachers as a team were considered a distinct teacher from either teacher working individually. For example, if John Doe and Richard Roe taught as a team, the team of John Doe and Richard Roe was considered a separate teacher from John Doe or Richard Roe teaching separately.

The student-teacher link data set also linked students to schools. Teacher is not nested within school; it is possible in the input data set for teachers to teach in multiple schools. The student-teacher link data set is merged with a second data set of student biographical data that identifies the schools students attended in the fall and spring of that year. This produces three points at which students are matched to school: one in the student-teacher link data set, and two--one each from the spring and the fall--from a separate student biographical data set.

A separate student-teacher link data set is used for charter schools. In the case of charter schools, teacher is nested within school.

Students are assigned to the school to which they are assigned in the student-teacher link data set, with several exceptions. First, if the school variable in the student-teacher link data set is blank, students are considered to have no school assignment. Second, if the school to which a student is assigned in the student-teacher link data set is different from either the spring or fall school from the student biographical data set, they are considered to have no school assignment, with two exceptions. First, students always have a school assignment if their classroom assignment was verified positively. Second, in 2004-05, students are assigned to the spring and fall school from the student biographical file provided the spring and fall schools are the same.

Students are assigned to the classroom within the school to which they are assigned in the student-teacher link data set, with similar exceptions. First, students with blank course numbers are considered not assigned to a classroom. Second, students for whom the student-classroom match was verified negatively are considered not assigned to a classroom. Third, students who are not assigned to a school are not assigned to a classroom.

Students are assigned to the teacher(s) in the student-teacher link data set to which their classroom assignment corresponds, with the following exceptions: students in classrooms with blank teacher IDs, teacher IDs of 000000, or teacher IDs of 999999; students in classrooms in which the classroom-teacher match is verified negatively; students for whom the student-classroom match is verified negatively; and students who are not assigned to a classroom or to a school.

In some cases, a teacher has only taught in the city for a short period of time before the tests are given. These teachers are re-coded as "part-year" teachers and given a different ID. This is done to avoid attributing student growth to teachers who have only been around for a short period of time. In the case of non-charter schools, a teacher is a "part-year" teacher if he was not yet teaching on the October 31 preceding the January ELA and March math tests. In the case of charter schools, a teacher is a "part-year" teacher if his start date at the charter school is after the October 31 preceding the January ELA and March math tests. Two exceptions are made to this rule. First, a teacher is never defined as "part-year" if his or her teacher-classroom match is verified positively. Second, teachers in team-teaching situations are never defined as "part-year".

Students are only included in analysis if they are successfully assigned to a school, classroom, and teacher. Students not assigned to a school, classroom, or teacher are not included in the value-added analysis.

Teacher experience

The data also includes a variable equal to the year of experience the teacher is in or expected to be or have been in on October 31. "Year of experience" is equal to years of experience plus one. A person who has taught for less than one year, for example, is in his first year of experience. A "part-year" teacher is, as of October 31, not yet in his or her first year of experience.

In the cases of teachers outside of charter schools, a teacher experience variable is produced from human resources data. The human resources data draws years, months, and days of teacher experience at three points in the year: once in September, once in November, and once in May. From these draws, implicit year of experience on October 31 is computed, presuming continuous experience during the school year and presuming that the draws were made on the first of the month. A teacher's year of experience is set using the November draw if possible. If the November draw is unavailable, the September draw is used. If neither the September nor the November draw is available, the May draw is used. If all three draws are unavailable, teacher experience is presumed to be unknown.

In the case of teachers in charter schools, year of experience is measured using the teacher's start date at the school, presuming continuous experience beginning at the teacher's start date at the school.

VALUE-ADDED MODEL

In New York, value added is measured in math and English Language Arts (ELA) in grades four through eight at the teacher level. Teachers receive single-year value-added measures that reflect student growth in 2008-09 as well as multiple-year value-added measures that reflect student growth over as many as four years. Value added results were also computed for student subgroups within a teacher's classrooms, such as students with disabilities, English language learners, and students in the top, middle, and lowest thirds of the population of all test-takers by prior achievement. The value-added model in New York measures average achievement among a teacher's students, controlling for prior achievement in both math and ELA and a large number of student and classroom characteristics.

The model, in brief

The value-added model is defined by four equations: a "best linear predictor" value-added model defined in terms of true student post and prior achievement and three measurement error models for observed post and prior achievement:

Student achievement: $y_{1i} = \zeta + \lambda y_{0i} + \lambda^{alt} y_{0i}^{alt} + \beta' X_i + \gamma' Z_i + \alpha' J_i + e_i$ (1)

Posttest measurement error: $Y_{1i} = y_{1i} + v_{1i}$ (2)

Same-subject pretest measurement error: $Y_{0i} = y_{0i} + v_{0i}$ (3)
Other-subject pretest measurement error: $Y_{0i}^{alt} = y_{0i}^{alt} + v_{0i}^{alt}$ (4)

where:

- y_{1i} is true post achievement;
- y_{0i} and y_{0i}^{alt} are true prior achievement in the same subject and in the other subject (math in the ELA model, ELA in the math model), with slope parameters λ and λ^{alt};
- X_i is a vector of characteristics of student *i*, with slope parameter vector β;
- Z_i is a vector of characteristics of student *i*'s classroom, with slope parameter vector γ;
- J_i is a vector of teacher indicators;
- α is a vector of teacher value-added effects (where α_j is the value-added effect for teacher *j*);
- e_i is the error in predicting post achievement given the explanatory variables included in the model;
- Y_{1i} is measured post achievement;
- v_{1i} is measurement error in post achievement;
- Y_{0i} and Y_{0i}^{alt} are measured prior achievement; and
- v_{0i} and v_{0i}^{alt} are measurement error in prior achievement.

Substituting the measurement error equations (2), (3), and (4) into the student achievement equation (1) yields an equation defined in terms of measured student achievement:

Measured achievement: $Y_{1i} = \zeta + \lambda Y_{0i} + \lambda^{alt} Y_{0i}^{alt} + \beta' X_i + \gamma' Z_i + \alpha' J_i + \varepsilon_i$ (5)

where the error term ε_i includes both the original error component and the measurement error components:

Error in measured achievement: $\varepsilon_i = e_i + v_{1i} - \lambda v_{0i} - \lambda^{alt} v_{0i}^{alt}$ (6)

Estimating the measured student achievement equation (5) without controlling for pretest measurement error yields biased estimates of all parameters, including the value-added teacher effects. This bias stems from the fact that measurement error in prior achievement causes the error term (6), which includes the measurement error components v_{0i} and v_{0i}^{alt}, to be correlated with measured prior achievement. The desired parameters, as defined in equation (1), can be estimated consistently if external information is available on the variance of measurement error for prior achievement; approaches for consistent estimation in the presence of measurement error are described in detail in Wayne Fuller, *Measurement Error Models* (Wiley, 1987). In New York, information about the variance of test measurement error is reported in the technical manuals for the New York State assessments and the 2005 NYC assessments.

When estimating the teacher effects, a shrinkage approach is employed to ensure that teachers with fewer students are not overrepresented among the highest- and lowest-value-added teachers due to randomness. The approach, Constrained Empirical Bayes shrinkage, is described in J. N. K. Rao, *Small Area Estimation* (Wiley, 2003).

Not only are overall teacher effects estimated, but so are teacher effects for student subgroups. These effects are produced by extending the above model to allow for teachers to have different effects for students with different characteristics. These extensions make it possible to produce teacher value added by pretest score, gender, English language learner, and disability.

The variables in the model

The student-level variables included in the model (the *X* variables in equation 1) include gender, race, English language learner (current and former), free- and reduced-price lunch, disability (by special education services recommended), summer school enrollment, absences and suspensions (lagged one year to avoid potential endogeneity problems), retained in grade before pretest year, change in school between pretest and posttest year, and new to city in pretest year. The classroom-level variables included in the model (the *Z* variables in equation 1) include class size, classroom averages of pretests and most of the student-level variables in *X* (variables were excluded if there was insufficient variation at the classroom level to measure a precise effect), and proportion of students in the classroom new to city in the posttest year (a variable excluded from *X* because of its rarity among individual students in the analysis sample).

Stage one regression (student-level regression)

The value-added regression is run in three stages. The first stage estimates the coefficients λ on the pretests and β on the demographic variables. It regresses posttest on same-subject pretest, other-subject pretest, student-level variables, and a full set of classroom fixed effects. This can be expressed mathematically as:

$$Y_{1i} = \lambda Y_{0i} + \lambda^{alt} Y_{0i}^{alt} + \beta' X_i + \alpha^{*\prime} C_i + \varepsilon_i$$

where C_i is a vector of classroom dummies that affect posttest with parameters α^*. For a given classroom c, α_c* is equal to $\zeta + \gamma' Z_c + \alpha_j$, where Z_c is the characteristics of classroom c and α_j is the value added of teacher j in classroom c.

This regression is estimated using an approach that accounts for measurement error in the pretests Y_{0i} and Y_{0i}^{alt}. Recall from equation (6) above that the measurement error components of Y_{0i} and Y_{0i}^{alt}, v_{0i} and v_{0i}^{alt}, are part of the error term ε_i. As a result, estimating the regression using ordinary least squares will lead to biased estimates. The regression approach employed accounts for measurement error by removing the variance in the pretests that is attributable to measurement error. To illustrate the measurement error corrected regression, re-cast the above value-added regression equation into vector form:

$$Y_t = Y_{t-1}\lambda + W\delta + \varepsilon$$

where Y_t is an N × 1 vector of post-test scores, $Y_{t\text{-}1}$ is an N × 2 vector of same-subject and other-subject pre-test scores $Y_{t\text{-}1}$ and $Y_{t\text{-}1}^{alt}$, λ is a 2 × 1 vector made up of λ and λ^{alt}, W is an N × K vector of the X demographic and C classroom attendance variables, δ is a K × 1 vector of the β and α^* coefficients, and ε is an N × 1 vector of error terms. The biased ordinary-least-squares estimates of the coefficients in λ and δ are equal to:

$$\begin{bmatrix} \hat{\lambda}_{OLS} \\ \hat{\delta}_{OLS} \end{bmatrix} = \begin{bmatrix} Y'_{t-1}Y_{t-1} & Y'_{t-1}W \\ W'Y_{t-1} & W'W \end{bmatrix}^{-1} \begin{bmatrix} Y'_{t-1}Y_t \\ W'Y_t \end{bmatrix}$$

The measurement-error-corrected estimates of the coefficients in λ and δ are equal to:

$$\begin{bmatrix} \hat{\lambda}_{CORR} \\ \hat{\delta}_{CORR} \end{bmatrix} = \begin{bmatrix} Y'_{t-1}Y_{t-1} - \sum_{i}^{N} sem_{it-1} & Y'_{t-1}W \\ W'Y_{t-1} & W'W \end{bmatrix}^{-1} \begin{bmatrix} Y'_{t-1}Y_t \\ W'Y_t \end{bmatrix}$$

where $sem_{it\text{-}1}$ is a 2 × 2 variance-covariance matrix of the errors of measurement of $Y_{it\text{-}1}$ and $Y_{it\text{-}1}^{alt}$ for student i. This model is described in section 2.2 of Wayne Fuller, *Measurement Error Models* (Wiley, 1987).

Stage two regression (classroom-level regression)

The second stage regression estimates the coefficients γ on the classroom-level variables. Let $q_{1i} = Y_{1i} - \lambda Y_{0i}$ - $\lambda^{alt} Y_{0i}^{alt}$ - $\beta' X_i$. Then we can express the second-stage regression mathematically as:

$$q_{1i} = \zeta + \gamma' Z_i + w_i$$

where w_i is equal to $\alpha' J_i + \varepsilon_i$. When estimating this regression, we have to use as our left-hand-side variable an estimate of q_{1i}, which is computed using the estimates of λ, λ^{alt}, and β from the first-stage regression. When this regression is run, it takes into account that the errors w_i are correlated within classrooms via $\alpha' J_i$ by specifying a classroom random effect.

Stage three regression (teacher-level value added)

Now that all the other variables have been controlled for, the third-stage regression estimates the value added measures α_j. This can be expressed using the equation

$$w_i = \alpha' J_i + \varepsilon_i.$$

where $w_i = Y_{1i} - \zeta - \lambda Y_{0i}$ - $\lambda^{alt} Y_{0i}^{alt}$ - $\beta' X_i$ - $\gamma' Z_i$. When we estimate this regression, it is necessary to use an estimate of w_i, which is drawn from the residuals of the second-stage regression.

This is a very easy regression to estimate. All one needs to do is compute the average of w_i within teachers j to produce estimates $\hat{\alpha}_j$. Once this is done, compute estimates of the error term ε_i by subtracting $\hat{\alpha}_j$ from the estimate of w_i. The standard errors of the estimates $\hat{\alpha}_j$ are equal to the square root of the ratio of the sample variance of the estimates of ε_i to the number of observations for teacher j. The variance-covariance matrix of $\hat{\alpha}$ is diagonal, and the n-weighted mean of $\hat{\alpha}_j$ across teachers is zero. It is important to note that the standard errors computed under this approach ignore error that comes from having used estimates of λ, β, and γ to control for pretests, student-level variables, and classroom-level variables rather than the true values of λ, β, and γ instead.

Single-year and multiple-year measures of value added

The three-stage regression described above is run separately for each combination of grade, subject, and year over four years of data. This produces unshrunk single-year teacher-level value added estimates in $\hat{\alpha}_j$. When we wish to measure a multiple-year measure of value added, we run the first two stages of the regression separately by year. When we come to the third stage, we pool our estimates of w_i over multiple years and compute the multiple-year versions of $\hat{\alpha}_j$ over the pooled data using the same technique as if it were a single-year estimate.

Shrinkage of teacher-level value added

The unshrunk value-added estimates $\hat{\alpha}_j$ are shrunk using a Constrained Empirical Bayes univariate shrinkage technique described in J. N. K. Rao, *Small Area Estimation* (Wiley, 2003).

The first step in shrinking the estimates $\hat{\alpha}_j$ is to estimate the variance of the true (rather than the estimated) teacher effects α_j. This is relatively straightforward. Let $\hat{\sigma}_j^2$ be the squared standard error of $\hat{\alpha}_j$. Also let $\hat{\omega}_{est}^2$ be the variance of $\hat{\alpha}_j$ across teachers. We estimate the variance of α_j as $\hat{\omega}^2 = \hat{\omega}_{est}^2 - \bar{\hat{\sigma}}_j^2$, where $\bar{\hat{\sigma}}_j^2$ is the mean of $\hat{\sigma}_j^2$ across teachers.

The second step in shrinking the estimates is to compute shrunk value-added estimates using simple Empirical Bayes shrinkage. This is accomplished by multiplying the unshrunk values added by their reliabilities. The estimated reliability of value added of teacher j is equal to $r_j = \hat{\omega}^2 / (\hat{\omega}^2 + \hat{\sigma}_j^2)$. Shrunk value added for teacher j is equal to $\hat{\alpha}_j^{EB} = r_j \hat{\alpha}_j$, and the standard error of shrunk value added is equal to $\hat{\sigma}_j^{EB} = r_j^{1/2} \hat{\sigma}_j$

The last step is to compute Constrained Empirical Bayes estimates from simple Empirical Bayes estimates. A Constrained Bayes estimate $\hat{\alpha}_j^{CB}$ multiplies a demeaned Empirical Bayes estimate by a fixed factor a:

$$\hat{\alpha}_j^{CB} = \overline{\hat{\alpha}}^{EB} + a\left(\hat{\alpha}_j^{EB} - \overline{\hat{\alpha}}^{EB}\right)$$

The fixed factor *a* is computed using the formula:

$$a = \left[1 + \frac{[1/J]\sum_j \left(\hat{\sigma}_j^{EB}\right)^2}{[1/(J-1)]\sum_j \left(\hat{\alpha}_j^{EB} - \overline{\hat{\alpha}}^{EB}\right)^2}\right]^{1/2}$$

where J is the total number of teachers. The squared standard error of the Constrained Bayes estimate $\hat{\alpha}_j^{CB}$ is equal to $\left(\hat{\sigma}_j^{CB}\right)^2 = \left(ar_j\right)^2 \hat{\sigma}_j^2 + \left(1 - ar_j\right)^2 \hat{\omega}^2$. Note that the rank order of teachers using Constrained Bayes estimates is the same as the order when using Empirical Bayes estimates.

Subgroups: ELL, special education, and gender

Value added is also estimated by subgroup. In a subgroup model, we assume that teachers have different effects for students with different characteristics. ELL is used as an example here, but the results generalize to special education and gender; pretest is a slightly different case discussed in the next section.

In the case of ELL, we replicate the student achievement model (1) with the following model:

$$y_{1i} = \zeta + \lambda y_{0i} + \lambda^{alt} y_{0i}^{alt} + \beta' X_i + \gamma' Z_i + \theta_0 J_i + \theta_1 [J_i \times (ELL_i - \mu_{ELL(j)})] + e_i \quad (1')$$

where θ_0 is a vector of J intercepts, θ_1 is a vector of J slopes, ELL_i is an indicator variable for student i being ELL and $\mu_{ELL(j)}$ is equal to the mean of ELL_i within teacher j.

When this is estimated, we impute the estimated ζ, λ, β, and γ from the first- and second-stage regressions in overall value added, leaving us with the estimated residual terms w_i previously used in computing overall value added. This residual term is regressed on (ELL_i - $\overline{ELL}_j$) within teachers, where $\overline{ELL}_j$ is the sample mean of ELL_i among teacher j's students. This yields estimates of the intercept $\hat{\theta}_{0j}$ and slope $\hat{\theta}_{1j}$ for each teacher j. Because the subgroup variable has been interpreted as a deviation from a mean, the estimate of the intercept $\hat{\theta}_{0j}$ is equal to the unshrunk estimate of overall value added $\hat{\alpha}_j$. The measurement error in the slope term, $\hat{\theta}_{1j}$, will be uncorrelated with the measurement error in the intercept term $\hat{\theta}_{0j}$, except for a component that derives from the substitution of $\overline{ELL}_j$ for $\mu_{ELL(j)}$ that is ignored.

The slope terms $\hat{\theta}_{1j}$ are shrunk using a Constrained Bayes approach that is the same as that described above for overall value added. When the variance of θ_{1j} is estimated for shrinkage, teachers for whom the standard error of $\hat{\theta}_{1j}$ is 0.5 or greater are excluded from the computation. These are badly measured estimates of $\hat{\theta}_{1j}$ that in some cases lead to negative estimates of the variance of θ_{1j}. The slope terms $\hat{\theta}_{1j}$ are demeaned before shrinkage to have a mean of zero across teachers within the group with a standard error small enough to be included in the variance computation.

From the shrunk overall value added estimate $\hat{\alpha}_j^{CB}$ and the shrunk slope $\hat{\theta}_{1j}^{CB}$ (both shrunk using Constrained Empirical Bayes), we compute value added among students both in and not in the subgroup. In the case of ELL, value added among ELL students for teacher *j* is equal to

$$\hat{\alpha}_j^{CB} + \hat{\theta}_{1j}^{CB}\left(1 - \overline{ELL}_j\right)$$

with a squared standard error equal to the squared standard error of $\hat{\alpha}_j^{CB}$ plus $\left(1 - \overline{ELL}_j\right)^2$ times the squared standard error of $\hat{\theta}_{1j}^{CB}$. This presumes that, across teachers, overall value added α_j and slope θ_{1j} are uncorrelated. Value added for non-ELL students for teacher *j* is equal to

$$\hat{\alpha}_j^{CB} - \hat{\theta}_{1j}^{CB}\,\overline{ELL}_j$$

with a squared standard error equal to the squared standard error of $\hat{\alpha}_j^{CB}$ plus $\overline{ELL}_j^{\,2}$ times the squared standard error of $\hat{\theta}_{1j}^{CB}$. Estimates of value added within subgroups are produced using a pooled sample that includes all four years of data as well as for 2008-09 only.

Subgroups: pretest

The differential model for pretest is conceptually the same as that for ELL and other variables. It can be written by replacing (1) in the overall value added model with

$$y_{1i} = \zeta + \lambda y_{0i} + \lambda^{alt} y_{0i}^{alt} + \beta' X_i + \gamma' Z_i + \theta_0 J_i + \theta_1 [J_i \times (y_{0i} - \mu_{y0i(j)})] + e_i \qquad (1'')$$

where $\mu_{y0i(j)}$ is the mean of pretest for teacher *j*. As is the case in the other subgroups, the intercept and slope estimates $\hat{\theta}_{0j}$ and $\hat{\theta}_{1j}$ are computed by regressing the residual estimate w_i on the demeaned-within-teacher pretest variable (Y_{0i} - $\overline{Y}_{0i|j}$) within teacher. Estimation is a little bit different, however, because of correlation between the measurement errors in w_i and (Y_{0i} - $\overline{Y}_{0i|j}$). In particular, if the squared standard error of measurement of Y_{0i} [and, it is presumed, (Y_{0i} - $\overline{Y}_{0i|j}$)] is σ_{err}^2, then the measurement error in w_i caused by same-subject pretest measurement error has a variance of $\lambda^2\sigma_{err}^2$. The covariance between the two errors is $-\lambda\sigma_{err}^2$. Within a single year, these are perfectly correlated measurement errors; when multiple years are pooled, the measurement errors are no longer perfectly correlated as λ differs across years.

To account for this measurement error, methods described in Section 3.1 of Wayne Fuller, *Measurement Error Models* (Wiley, 1987) are employed. These approaches take into account correlated measurement errors across the left- and right-hand-side variables in a regression, as well as improving moment properties in small within-teacher samples.

After $\hat{\theta}_{0j}$ and $\hat{\theta}_{1j}$ are computed using these methods, it is the case that $\hat{\theta}_{0j}$ is equal to overall unshrunk value added $\hat{\alpha}_j$. The measurement errors of the unshrunk slopes $\hat{\theta}_{1j}$ are uncorrelated with those of unshrunk intercepts $\hat{\theta}_{0j}$ except for a component derived from substituting the within-teacher sample means $\bar{Y}_{0i|j}$ for the actual means $\mu_{y0i(j)}$). This component is ignored. The slopes $\hat{\theta}_{1j}$ are shrunk using Constrained Empirical Bayes shrinkage to produce shrunk slopes $\hat{\theta}_{1j}^{CB}$.

Value added for teacher *j* among students in the citywide top third is equal to

$$\hat{\alpha}_j^{CB} + \hat{\theta}_{1j}^{CB}\left(\bar{Y}_{0i|j,top} - \bar{Y}_{0i|j}\right)$$

where $\bar{Y}_{0i|j}$ is the average pretest score of students taught by teacher *j* and $\bar{Y}_{0i|j,top}$ is the average pretest score of students taught by teacher *j* in the citywide top third. The squared standard error of value added for the top third is equal to the squared standard error of $\hat{\alpha}_j^{CB}$ plus $\left(\bar{Y}_{0i|j,top} - \bar{Y}_{0i|j}\right)^2$ times the squared standard error of $\hat{\theta}_{1j}^{CB}$. This approach implies that, across teachers, the true parameters α_j^{CB} and θ_{1j}^{CB} are uncorrelated. Value added for the middle and bottom third are computed analogously; value added for all three thirds are computed using both the 2008-09 sample only and using the full four-year sample.

REPORTING VALUE ADDED

After the value-added analysis is completed, each teacher has a large number of results about the improvement of his or her students. Each teacher in the tested grades has a single-year overall value added that covers 2008-09; a multiple-year overall value added that covers 2005-06, 2006-07, 2007-08, and 2008-09; single-year value-added measures for 2008-09 specific to students with disabilities, ELL students, male students, female students, and students in the top, middle, and bottom thirds of the pretest distribution; and multiple-year value-added measures that cover the same subgroups for all four years.

These results need to be prepared in a way that can be digested by teachers and principals. Each teacher in the tested grades with enough students in the value-added analysis data set to draw inferences receives a report of his or her value added. If he or she taught in multiple grades or multiple subjects; he or she receives a separate report for each subject and grade. Principals also receive value added reports that present the value-added results of teachers in the school in 2008-09.

Confidence intervals

The value-added measure is our best estimate of the teacher's effects on his or her students given the data, and is often referred to as a *point estimate* given that it is a single number. However, every value-added measure is based on a finite number of students and, consequently, includes some error from randomness in the students a teacher has.

In reports, value added is presented as a point estimate surrounded by a 95 percent confidence range. The maximum point within this range is equal to the value-added point estimate plus 1.96 times the standard error of value added. The minimum point is equal to the point estimate minus 1.96 times the standard error of value added. Values outside of this range can be rejected with 95 percent confidence as the teacher's value added score.

Converting value added to proficiency units

Value added is computed using z-scores, in which value added is measured in student-level standard deviation units. For presentation, value added is converted to a scale similar to the proficiency ratings used in the DOE's Progress Reports.[2] To accomplish this, the mean and standard deviation of proficiency ratings across students within grade is computed for the 2008-09 school year. Value added in z-score is converted to value added on a proficiency rating scale by multiplying value added in z-score by the standard deviation of proficiency ratings across students within grade. This is not an exact conversion to the proficiency scale, which is a non-linear transformation of scale score. Instead, it is a linear approximation of that conversion.

Computing prior proficiency, actual score, and predicted score

For reporting, average proficiency rating in the pretest year and the posttest year is computed for each teacher within the sample used to produce value added. Predicted posttest score is computed as average posttest proficiency rating minus value added converted to the proficiency scale. This predicted score is actually a counterfactual score; it is what we would expect the average student's score to have been had he attended a randomly selected classroom in the city. The counterfactual presumes that the linear transformation of value added based on z-scores to value added based on proficiency ratings is a good approximation of the non-linear transformation actually used to transform scale scores to proficiency ratings. The predicted score is bounded by 1.0 and 4.5, which are the minimum and maximum proficiency ratings.

[2] For more information about the New York City Progress Reports go to: http://schools.nyc.gov/Accountability/SchoolReports/ProgressReports/default.htm

Computation of percentiles

Citywide percentile ranking of overall value added

Citywide percentile ranks are computed for overall value added for 2008-09. These percentile ranks are computed only over teachers with at least six students in 2008-09. This relatively light suppression rule is used to put a large number of teachers into the percentile ranking so that the mapping of value added score to percentile ranking is sufficiently granular to have meaning. The percentile ranking is computed on an unweighted basis.

Citywide percentile ranks are also computed for the minimum and maximum of the 95 percent confidence range of overall value added for 2008-09. These are computed by taking the minimum and maximum of the confidence interval range for a given teacher and finding where they fall on the mapping of overall value added to percentile ranks.

Citywide percentile ranks are computed for multiple-year overall value added in the same way in which they are computed for value added for 2008-09 only. These percentile ranks are computed over teachers with at least one student in 2008-09 and at least six students over all four years covered by multiple-year value added.

Percentile ranking within experience level

Percentile ranks for overall value added are also computed for both 2008-09 and multiple years within different levels of experience. Percentile ranks are computed within four levels: one year, two years, three years, and more than three years. In these cases, percentile ranks reflect comparisons with teachers of similar experience only. Percentile rankings within experience level are not produced for cases of team teaching or for cases in which teacher experience is unavailable.

Percentile and subgroups

Percentile ranks for subgroups are computed by applying the percentile distribution of overall value added to subgroup value added. Consequently, a value at, say, the 76th percentile for overall value added is also at the 76th percentile for subgroup value added. This is not a true percentile ranking in the technical sense; rather, it is a mapping that is the same across the overall and subgroup value added to make interpretation of results easier. The percentile distribution of overall value added for 2008-09 is applied to subgroup value added computed from the 2008-09 sample only, while the percentile distribution of multiple-year overall value added is applied to subgroup value added computed from the full four-year sample.

Reporting value added

Teacher level value added results are most useful when they are based on enough students to draw conclusions about their growth in a teachers classroom. Consequently, value added is only reported if a teacher had a sufficient number of students.

Overall value added for 2008-09 was reported only if a teacher had at least 10 students in 2008-09. In English language arts in grades 6 through 8, this was raised to 20 students; preliminary findings suggested that larger sample sizes were needed in these grades to produce value-added results with reasonably high reliabilities. Only teachers who met the criteria to receive a value-added score for 2008-09 received a report.

Multiple-year overall value added was reported if a teacher had at least 10 more students over the four-year period spanning 2005-06, 2006-07, 2007-08, and 2008-09 then he or she did in 2008-09 alone. In most cases, this means that multiple-year value added was reported for teachers with at least 10 students in 2008-09 and at least 20 students over the full four-year period. The exception is English language arts in grades 6 through 8, where multiple-year value added was reported for teachers with at least 20 students in 2008-09 and at least 30 students over the full four-year period.

When reported, multiple-year value added was reported for the span of time actually covered by the students assigned to the teacher in the data set. If a teacher had students in 2005-06 included in the value-added results, multiple-year value added was reported as value added for the past four years. If he or she did not have students in 2005-06 but had students in 2006-07, it was reported as value added for the past three years. If he or she only had students in 2007-08 and 2008-09, it was reported as value added for the past two years.

If a teacher received multiple-year value added on his or her report, reported values of subgroup value added were the subgroup results for the full four-year period. If a teacher only received overall value added for 2008-09 on his or her report, reported values of subgroup value added were the subgroup results for 2008-09 only. Either way, subgroup value added was only reported if a teacher had 10 students or more in the subgroup being reported. This criterion was raised to 20 students in the case of English language arts in grades 6 through 8.

Value added percentiles within teacher experience categories were included in the reports. Citywide percentiles were only reported for teachers who were in team-teaching situations or for teachers for whom experience was unavailable. Each value added measure reported was assigned to one of five categories based on reported percentile: "low" (0th through 4th percentiles); "below average" (5th through 24th percentiles); "average" (25th through 74th percentiles); "above average" (75th through 94th percentiles); and "high" (95th through 99th percentiles).

PROPERTIES OF THE VALUE-ADDED RESULTS

Coefficients on student- and classroom-level variables in the model

The coefficients estimated in the value-added model for a single grade, subject, and year (grade 5 math for 2008-09) are presented below. To interpret the below coefficients, note that both pretest (4th grade tests in math and ELA) and posttest (5th grade test in math) are measured using z-scores with a mean of 0 and a standard deviation of 1 across students in New York City. Consequently, all coefficients are measured in student-level standard deviations. For example, note that the coefficient on female gender is -0.02. This implies that female students improved 0.02 standard deviations less on the New York State math test from 2007-08 to 2008-09 than otherwise similar male students. On the fifth grade math test in 2008-09, a standard deviation is equal to about 35 scale score points. By comparison, the difference between the performance level cuts for Level II (619) and Level III (650) is 31 scale score points, and that between Level III (650) and Level IV (699) is 49 points.

Coefficients on student-level variables, 5th grade math, 2008-09

Variable	*Coeff.*	*Std. Err.*
Math pretest	0.68	(0.01)
ELA pretest	0.11	(0.01)
Female	-0.02	(0.00)
Asian	0.10	(0.01)
Black	-0.06	(0.01)
Native American	0.04	(0.04)
White	0.04	(0.01)
Other race	-0.07	(0.05)
ELL	0.02	(0.01)
Former ELL	0.03	(0.01)
Disability: related services	-0.02	(0.02)
Disability: self-contained	-0.10	(0.03)
Disability: teacher support	-0.09	(0.01)
Disability: team teaching	-0.10	(0.02)
Free lunch	-0.01	(0.01)
Reduced-price lunch	-0.02	(0.01)
Summer school	0.03	(0.01)
Log absences	-0.03	(0.00)
Log suspensions	-0.03	(0.04)
Retained in grade before pretest year	-0.05	(0.02)
Same school in pretest and posttest years	-0.03	(0.01)
New to city in pretest year	0.08	(0.01)

The coefficients below are coefficients on the classroom variables in the model. These measure the relationship between classroom characteristics and student improvement on the test. For example, the coefficient on proportion free lunch is -0.03. This means that a 10 percentage point increase in the share of free-lunch students in the classroom (say, from 50 percent to 60 percent) is associated with a 0.003 (10 percent of 0.03) standard deviation decrease in the scores of students in that classroom, regardless of whether the students are free-lunch or not.

Coefficients on classroom-level variables, 5th grade math, 2008-09

Variable	*Coeff.*	*Std. Err.*
Average math pretest	-0.07	(0.02)
Average ELA pretest	0.04	(0.02)
Class size	-0.002	(0.001)

Indicator for class size less than 6[3]	-0.02	(0.05)
Proportion female	0.10	(0.04)
Proportion Asian	0.01	(0.03)
Proportion black	-0.05	(0.02)
Proportion white	0.01	(0.03)
Proportion ELL	-0.01	(0.03)
Proportion former ELL	0.04	(0.09)
Proportion w/disability: related/support	-0.06	(0.06)
Proportion w/disability: self-contained	-0.10	(0.03)
Proportion w/disability: team teaching	-0.04	(0.05)
Proportion free lunch	-0.03	(0.02)
Proportion reduced-price lunch	0.13	(0.06)
Proportion summer school	-0.13	(0.04)
Average log absences	-0.04	(0.02)
Proportion retained before pretest year	0.13	(0.13)
Proportion same school pretest/posttest	0.27	(0.03)
Proportion new to city in posttest year	-0.03	(0.09)
Proportion new to city in pretest year	0.21	(0.09)

It is important to keep in mind the standard errors of the coefficients in both the student- and classroom-level models when interpreting them. A span of two standard deviations in both the positive and negative directions provides a 95 percent confidence range for a coefficient. For example, note that the coefficient on proportion free lunch is -0.03. The standard error on this coefficient is 0.02. This means that, while our best estimate of the effect of proportion free lunch on classroom-wide growth is -0.03 standard deviations, a 95 percent confidence range for the effect estimate would range from -0.07 to +0.01 standard deviations. Since this range includes zero, we cannot reject with 95 percent confidence the hypothesis that proportion free lunch has no effect on student improvement in the classroom.

It is also important to note that the variables indicating new to city in posttest year and new to city in pretest year do not just include the effects of being new to the city, but also the effect of having students in the classroom with missing data for several of the variables in the posttest and pretest years. Consequently, interpretation of those coefficients should be made with caution.

Correlation with average prior proficiency

Value-added results show a very low correlation between average prior proficiency--a measure of average performance in the previous year among the teacher's students--and value added. In general, teachers were no more or less likely to have a low

[3] The indicator for class size less than 6 is included in the model because class size is bottomcoded at 6.

value added than a high one if their students came in with low pretest scores rather than high ones.

Correlations between value added and average prior proficiency

	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
2008-09 math value added	0.00	-0.03	0.00	-0.06	0.00
Multi-year math value added	-0.01	-0.02	0.01	-0.04	0.01
2008-09 ELA value added	0.03	0.04	0.00	-0.01	-0.01
Multi-year ELA value added	-0.01	0.02	0.00	-0.04	-0.03

Stability

Another property of the value-added results was stability over time. Teachers that were high value added in one year were, more often than not, also high value added in the following year. In general, value added in 2008-09 had a substantively positive correlation with value added in 2007-08, particularly in math.

Correlation between 2007-08 and 2008-09 value added

	Math	ELA
Grade 4	0.48	0.24
Grade 5	0.45	0.33
Grade 6	0.62	0.24
Grade 7	0.50	0.20
Grade 8	0.59	0.24

Correlation between math and ELA value added

There were also substantive positive correlations between math and ELA value added among teachers who taught both math and ELA in the same grade. Teachers who were high value added in math were also more often than not also high value added in ELA when they taught both subjects.

Correlation between math and ELA value added, same teachers

	2008-09 value added	Multi-year value added
Grade 4	0.52	0.55
Grade 5	0.39	0.49
Grade 6	0.41	0.48

Range of value added

Value added scores are reported below not as z-scores, but rather on a scale that is a linear transformation of the z-scores that has the same variance as widely-used proficiency ratings in New York City. The reported value-added scores frequently have a wider range in math than in English language arts. For example, the difference between the citywide 25th and 75th percentiles was 0.18 in fifth grade math and 0.10 in fifth grade

ELA. This is because both the range of value added in z-scores and the variance of proficiency ratings in New York City is tighter in English language arts than in math.

Ranges of value added (proficiency ratings), citywide 25th to 75th percentiles

	Range of 2008-09 ELA VA			Range of multi-year ELA VA		
Grade	25th	75th	Range	25th	75th	Range
4	-0.08	0.07	0.15	-0.06	0.06	0.13
5	-0.06	0.04	0.10	-0.05	0.04	0.10
6	-0.05	0.04	0.08	-0.04	0.04	0.08
7	-0.03	0.03	0.06	-0.03	0.03	0.06
8	-0.04	0.04	0.09	-0.03	0.04	0.07

	Range of 2008-09 math VA			Range of multi-year math VA		
Grade	25th	75th	Range	25th	75th	Range
4	-0.11	0.10	0.21	-0.09	0.09	0.18
5	-0.09	0.09	0.18	-0.08	0.09	0.17
6	-0.11	0.10	0.21	-0.10	0.10	0.19
7	-0.07	0.06	0.13	-0.07	0.06	0.13
8	-0.09	0.10	0.20	-0.09	0.09	0.18

Ranges of value added (proficiency ratings), citywide 5th to 95th percentiles

	Range of 2008-09 ELA VA			Range of multi-year ELA VA		
Grade	5th	95th	Range	5th	95th	Range
4	-0.18	0.19	0.37	-0.15	0.17	0.32
5	-0.13	0.18	0.31	-0.12	0.14	0.26
6	-0.11	0.13	0.24	-0.10	0.10	0.20
7	-0.08	0.09	0.17	-0.07	0.08	0.15
8	-0.11	0.11	0.22	-0.09	0.09	0.18

	Range of 2008-09 math VA			Range of multi-year math VA		
Grade	5th	95th	Range	5th	95th	Range
4	-0.25	0.30	0.56	-0.22	0.26	0.48
5	-0.23	0.26	0.49	-0.21	0.24	0.44
6	-0.26	0.29	0.55	-0.23	0.27	0.50
7	-0.16	0.19	0.35	-0.15	0.17	0.32
8	-0.25	0.26	0.51	-0.21	0.24	0.45

CONCLUSION

This technical report described the value-added model used in the NYC Department of Education and developed in association with the Value-Added Research Center of the Wisconsin Center for Education Research at the University of Wisconsin.

For more information on the value-added research of the Value-Added Research Center of the Wisconsin Center for Education Research at the University of Wisconsin, visit VARC's website at:

http://varc.wceruw.org/

For information on how the NYC Department of Education guidance to schools for how to use this data, see the Teacher Data Toolkit on the NYCDOE webpage at:

http://schools.nyc.gov/Teachers/TeacherDevelopment/TeacherDataToolkit/default.htm