

Stanford Education Data Archive Technical Documentation

SEDA 2024

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What is SEDA2024?

The Stanford Education Data Archive (SEDA) is created by the Educational Opportunity Project (EOP) at Stanford University (<https://edopportunity.org>). The EOP aims to generate and share data and research that can help scholars, policymakers, educators, and parents learn how to improve educational opportunities for all children. SEDA is the flagship data product of the EOP; it showcases how state accountability test data can be used to study educational opportunity in the U.S.

SEDA2024 is a special release of the Stanford Education Data Archive. This release is designed to provide insight into how school district average achievement changed before, during, and after the COVID-19 pandemic.

Acknowledgements

Data construction was supported by a grant from the Gates Foundation. The source data used to construct our estimates come from Zelma, the National Center for Education Statistics (NCES), and the National Assessment Governing Board. The findings and opinions expressed in our research and reported here are those of the authors alone; they do not represent the views of the U.S. Department of Education, NCES, Zelma, or the Gates Foundation.

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Data Use Agreement

Prior to downloading the data, users must sign the data use agreement (<https://edopportunity.org/get-the-data/>).

I. Achievement Data Construction

I.A. Overview of Test Score Files

SEDA 2024 contains test score data files for administrative school districts and states. Test score data files contain information about the average academic achievement as measured by standardized test scores administered in 3rd through 8th grade in mathematics and Reading Language Arts (RLA) over the 2008-09 through 2023-24 school years.

We released twenty-four test score files corresponding to the two units (administrative school districts and states) by four scales (CS, GCS, YS, GYS) by three pooling levels (long, annual by subject, and annual). “Long” files contain estimates for each grade and year separately; “annual by subject” (or annualsub) files contain estimates for each year pooled over grades within subject; and “annual” files contain estimates for each year pooled over grades and subjects. In the long files there are variables corresponding to test score means by subgroup and their respective standard errors in each grade, year, and subject. In the annualsub files, there are variables corresponding to the average test score means by year in math and in RLA (averaged over grades). In the annual files, there are variables corresponding to the average test score mean by year (averaged over grades and subjects). Estimates are reported for all students and by demographic subgroups. [Table 1](#) shows the test score files available in this release.

I.B. Source Data

State Accountability Test Data

We use state accountability data from two primary sources: (1) the *EDFacts* data system; and (2) state-reported accountability data from Zelma.

EDFacts

The *EDFacts* data system collects aggregated test score data from each state’s standardized testing program as required by federal law. Specifically, each state is required to test every student in grades 3 through 8 in math and Reading Language Arts (RLA) each year. States have the flexibility to select or design a test that measures student achievement relative to the state’s standards. Additionally, states set their own benchmarks or thresholds for the levels of performance, e.g., “proficient,” in each grade and subject. States select 2 to 5 performance levels, where one or more levels represent “proficient” grade-level achievement. To *EDFacts*, states report the number of students in each school, subgroup, subject, grade, and year scoring at each of their defined performance levels. *No individual student-level data are reported.*

EDFacts data on school assessment outcomes are available for eleven consecutive school years from 2008-09 through 2018-19 in grades 3 to 8, and one grade in high school, in RLA and math.¹ The student subgroups include race/ethnicity, gender, and socioeconomic disadvantage, among others. The raw EDFacts data used in SEDA include no suppressed cells, nor do they have a minimum cell size for reporting. The data are reported by school, subject, grade, year, and subgroup and include schools in every state.

State-reported accountability data.

We supplement the EDFacts data with state-reported data for 2021-22 through 2023-24. Most states publicly report their school and/or district proficiency data as part of federal accountability. These data have been compiled by Zelma (www.zelma.ai) into a single public database. To use data for a given state-subject-grade-year, we require:

- (1) The data must be disaggregated by school or school district, subgroup, subject, grade, and year.
- (2) Data must be reported in at least three proficiency categories.

States reported useable data in three common patterns:

- (1) Number of students scoring in each proficiency category. These are the necessary student-level data and were used “as is.”
- (2) Total number of students tested and the percent scoring in each proficiency category. From these data, we derived the counts in each category (with some rounding error).
- (3) Only the percent scoring in each proficiency category. We estimate the total number of test takers (in each school district, subgroup, subject, grade, and year) using the Common Core of Data (CCD).² We then derived an estimated count scoring in each category. In the downloadable data files, we flag all cells where we estimated counts.

Additionally, not all states reported data for all subgroups. States also used different suppression rules to protect student privacy. Some states suppress entire rows of data that do not meet reporting thresholds typically based on sample size, while others use partial suppression (suppressing some cells of data within a row). The extent and type of suppression affected our methodology for estimating district

¹ Data are also available for the 2020-21 and 2021-22; however, they are not reported in sufficient detail for our use. Data for 2022-23 and 2023-24 are not yet available.

² Specifically, we estimate the number of test takers in a district-subgroup-subject-grade as the number of enrolled students in the district-subgroup-subject-grade from the CCD in the fall of the school year. For example, we use 2023 CCD data to estimate the tested count in Spring 2024. If the number of enrolled students is missing for a given district-subgroup-grade, then imputed values are used.

average scores and sometimes prohibited our ability to produce estimates for individual districts. [Table 2](#) provides a summary of data available from states in 2022-2024.

National Assessment of Educational Progress Data

We also draw on the National Assessment of Educational Progress Data (NAEP) 2009-2024 national and state assessment data in 4th and 8th grade math and reading.³ We use the state data to: (1) construct state-subject-grade-year mean estimates; and (2) to link the estimates derived from the state accountability data to a common scale.⁴ We use the national NAEP data to scale the data to interpretable units, including standard deviations relative to a national reference cohort and grade-equivalents.

Common Core of Data

Because some of the state accountability data does not report student counts, we also draw on the 2021-2023 Common Core of Data (CCD; <https://nces.ed.gov/ccd/>). From the CCD, we use the counts of students by grade and subgroup for districts and states.

I.C. Definitions and Notation

Definitions

Administrative School District: Administrative school districts operate sets of public and charter schools. The schools operated by each school district are identified using the NCES school and district identifiers. Most commonly, administrative school districts operate local public schools within a given physical boundary; these are what we refer to as “traditional public school districts.” There are also specialized administrative districts that do not have a physical boundary, like charter school and virtual school districts.

Group: The term “group” refers to a unit-subgroup.

State: States are identified by their FIPS state code. We include all 50 states plus Washington, DC.

³ We use the Expanded Population Estimates (EPEs) in 2009-2022. We do not have EPEs in 2024, so we created adjustments based on historical NAEP data to apply to the 2024 regular NAEP means and SDs. These are shown in the table below.

Subject	Grade	Mean Adjustment	SD Adjustment
Math	4	- .7579991	+ .5540244
Math	8	- .9166223	+ .5968
Reading	4	- 1.120848	+ .7713522
Reading	8	- 1.186662	+ 1.005793

⁴ Because different states use different tests and proficiency thresholds, the test score estimates derived from the above data sources are not readily comparable across states, grade, or years. Using NAEP allows us to put all test scores on a common scale that can be compared across states, grades, and years.

Subcategory: The term “subcategory” refers to the subcategory to which a subgroup belongs. In addition to data for all students, we have data for the following subcategories: gender, race, and economic status. The gender subcategory contains two subgroups, male and female. The race subcategory includes the Asian, Black, Hispanic, Native American, and White subgroups. The economic status subcategory includes the economically disadvantaged (ECD) and not economically disadvantaged (non-ECD) subgroups.

Subgroup: The term “subgroup” refers to the group of students to which an estimate pertains. Subgroups include: all, Asian, Black, Hispanic, Native American, White, female, male, economically disadvantaged (ECD), and not economically disadvantaged students (non-ECD).

Unit: The term “unit” refers to the aggregation of the data, e.g., administrative school district or state.

Notation

- Test score estimates are denoted as $\hat{\mu}$. Their standard errors are denoted as $se(\hat{\mu})$.
- A subscript indicates the aggregation of the estimate. We use the following subscripts:
 - u = unit (generic)
 - d = administrative school district
 - s = state
 - N = national
 - h = subgroup
 - all = all students
 - blk = Black
 - hsp = Hispanic
 - wht = White
 - ecd = economically disadvantaged
 - nec = not economically disadvantaged
 - y = year
 - b = subject
 - g = grade
- A superscript indicates the scale of the estimate. The metric is generically designated as x . There are six scales. The first two scales are only used in construction. The latter four scales are reported:
 - n = NAEP metric
 - s = state metric
 - cs = cohort scale metric
 - ys = year scale metric
 - gcs = grade within cohort scale metric
 - gys = grade within year scale metric
- An asterisk (*) indicates an Empirical Bayes (shrunken) estimate. The absence of an asterisk indicates a least squares (OL) estimate.

I.D. Construction Detail

We construct the data in a series of steps. The estimation process is conducted separately for data from each source (EDFacts vs. Zelma); however, the process is largely identical. When the two processes differ, it is noted below.

Step 1: Applying the School-to-District Crosswalk

2009-2019 Data. For SEDA 5.0, we developed stable public school identifiers and a crosswalk that uniquely links each stable school ID to an administrative school district (e.g., NCES leadid) in 2009-2019. We use the CCD's *Public Elementary/Secondary School Universe Survey Data* (Directory and School Characteristics files) and the *Local Education Agency (School District) Universe Survey Data* (Directory files) and other geographic units. See the SEDA 5.0 Technical Documentation for more detail on the crosswalk construction. We made a small number of updates to the SEDA 5.0 crosswalk for SEDA 2024, including moving some schools that closed prior to the Detroit school district ID change into the new school district and minor name changes. We apply the updated crosswalk to the 2009 to 2019 data to get counts of students scoring in each proficiency category by administrative district and state. The crosswalk is available for download on our website.

2022-2024 Data. A school-to-leaid crosswalk is not needed in 2022-2024 as the proficiency data are already reported for administrative districts and states.⁵

Note that we only report data in this release by state and administrative school districts because the 2022 through 2024 data is insufficient to construct other units (e.g., geographic school districts, counties, etc.). Specifically, complete school-subject-grade-year data is required. While many states report such data in 2022, data for many schools is suppressed due to the small numbers of students taking assessments. Because of this we cannot reliably construct estimates in 2022 through 2024 for other units. While we can construct other units in 2009-2019 and may do so as part of our estimation process, for consistency we only publicly report estimates for administrative districts and states.

Step 2: Data Cleaning

This step removes data not used in data construction and prepares the data for cutscore estimation.

⁵ While many states report data by school in 2022-2024, there is too much suppression to reliably construct district estimates from the school level data in most states. Because of this, it is possible that the set of schools assigned to a given district in 2019 is not identical to that in later years. We acknowledge this limitation.

State-subject-grade-year removals. [Table 3a](#) shows the state-grade-year-subjects for which we produce estimates. [Table 3b](#) shows why estimates are not available when they are not. There are two primary reasons why a state-subject-grade was removed from the data prior to estimation:

1. Test participation in a state-subject-grade-year was too low. We use a threshold of 94% state-wide participation and remove any state-subject-grade-year where the 2009-2019 participation rate falls below this threshold. For 2022-2024, we use participation rate data when it is available. If it is unavailable, we assume that the participation rate exceeds 94%.
2. More than 5% of students took a test that is not the primary grade-level state assessment used for accountability. This occurs for two reasons. First, in some states students may take an end-of-course assessment. This is common in 8th grade math, when a subset of students takes the Algebra I test in place of the 8th grade math assessment. Second, a Spanish-language version of an assessment may be used in some subjects and grades. Spanish- and English-language versions of the assessments are not always equivalent, particularly when assessing reading and language skills. Because our estimation methodology relies on the fact that all students took a common test (within a state-subject-grade-year), we remove cases where fewer than 95% of students took the primary state accountability assessment for a given state-year-subject-grade. We identified these cases using two types of information:
 - a. State-reported information on the number of students taking each type of assessment. If more than 5% of students were reported to take the non-primary test in a subject-grade-year cell, it was removed.
 - b. State-level data on the number of students tested by grade-subject. If the reported number tested in a grade-subject-year cell was substantially lower than other grade subjects in the same year (suggesting a lower testing rate), it was removed.

Data cleaning. For the 2009-2019 data, we combine performance data for regular and alternate assessments. See the SEDA 5.0 documentation for additional details. For 2022-2024, we use data as reported, which may or may not include alternative assessments.

Step 3: Estimating Cutscores

2009-2019 data. We estimate state-grade-subject-year cutscores for the 2009 to 2019 years using the HETOP estimation methodology outlined in the SEDA 5.0 Technical Documentation.

2022-2024 data. We estimate state-grade-subject-year cutscores for the 2022 to 2024 years using the inverse cumulative standard normal distribution function. Specifically, using the state-subject-

grade-year counts for all students, we estimate the k th cutscore in the state-subject-grade-year as (subject, grade, year subscripts omitted):

$$c_{ks} = \Phi^{-1}(p_{ks}) \quad (3.1)$$

where p_{ks} is the proportion of students scoring below the k th cutscore in the state-grade-subject-year.

For all years of data, we disattenuate the cutscores for test reliability using the following formula:

$$c_{ks}^{s'} = \frac{c_{ks}}{\sqrt{r_s}} \quad (3.2)$$

where r_s is the reliability of the state test in the given subject-grade-year.

Notably, unlike SED 5.0, we do not link the cutscores prior to mean estimation. Thus, at the end of this step, we have cutscores on the state-standardized metric for all state-subject-grade-years with sufficient data from 2009 to 2024. These cutscores are not comparable across states, subjects, grades, or years.

Step 4: Selecting and Preparing Data for Mean Estimation

This step selects data for unit-subgroup-subject-grade-year cases that will be used in mean estimation. The rules are as follows:

1. The participation rate is less than 94%. In these cases, the population of tested students on which the mean and standard deviation estimates are based may not be representative of the population of students in that school. For 2022-2024, we use participation rate data when it is available. If it is unavailable, we assume that the participation rate exceeds 94%.
2. Incomplete data reported by student demographic subgroups. There are a small number of cases where the total number of test scores reported by race is less than 95% of the total reported test scores for all students. We are concerned about subgroup data quality in these cases. We can only use this rule in 2009-2019.
3. More than 40% of students take alternate assessments. Measurement error may affect district-subgroup-subject-grade-year cases where students take alternate assessments. These assessments typically differ from the regular assessment and generally have different proficiency thresholds or meanings. The threshold for exclusion is 40%. We can only use this rule in 2009-2019.
4. Students scored only in the top or only in the bottom proficiency category. We cannot obtain maximum likelihood estimates of unique means for these cases and therefore remove them prior to estimation.

5. District-subgroup-subject-grade-year cells that do not meet the minimum statistical estimation requirements. When all cells for a district are insufficient (e.g., have all observations in a single middle category; have all observations in only 2 adjacent categories; have only 2 proficiency categories (one cutscore); or have all observations in only the top and bottom categories) or small (have fewer than 100 test scores) we do not have sufficient information to produce mean and standard deviation estimates.

Step 5: Estimating Means

State-All Student Estimates. The state estimates we report for the all student group come from the main NAEP state data, not state accountability data. NAEP data provide estimates of 4th and 8th grade test score means and standard deviations for each state on a common scale, denoted $\hat{\mu}_{sygb}^n$ and $\hat{\sigma}_{sygb}^n$, respectively, as well as their standard errors.⁶ Because NAEP is administered only in 4th and 8th grades in odd-numbered years from 2009 to 2019 and even years from 2022 to 2024, we interpolate and extrapolate linearly to obtain estimates of these parameters for grades (3, 5, 6, and 7) and years (2010, 2012, 2014, 2016, 2018, 2023) in which NAEP was not administered. First, within each NAEP-tested year (2009, 2011, 2013, 2015, 2017, 2019, 2022 and 2024) we linearly interpolate between grades 4 and 8 to grades 5, 6, and 7 and extrapolate to grade 3. Next, for all grades 3-8, we linearly interpolate between the odd NAEP-tested years to estimate parameters in 2010, 2012, 2014, 2016, 2018, and 2023 using the interpolation/extrapolation formulas here:

$$\begin{aligned}\hat{\mu}_{sygb}^n &= \hat{\mu}_{sy4b}^n + \frac{g-4}{4}(\hat{\mu}_{sy8b}^n - \hat{\mu}_{sy4b}^n), \\ &\text{for } g \in \{3, 5, 6, 7\} \\ \hat{\mu}_{sygb}^n &= \frac{1}{2}(\hat{\mu}_{s(y-1)gb}^n + \hat{\mu}_{s(y+1)gb}^n), \\ &\text{for } y \\ &\in \{2010, 2012, 2014, 2016, 2018, 2023\}\end{aligned}\tag{5.1}$$

We use the same formulas to interpolate the standard deviations. At the end of this step, we have estimates, on a common scale, for all states plus the District of Columbia in all grades and years. Note, however, that the count of students tested associated with each estimate we report do not come from NAEP. We use the counts from ED*Facts* in 2009 to 2019 and Zelma or CCD (in 2022 to 2024).

⁶ Note that the NAEP scales are not comparable across math and reading, but they are comparable across states, grades and years within each subject.

State-Subgroup and District Estimates. For all other estimates, we use the pooled HETOP model to estimate district-subgroup-subject-grade-year means and standard deviations, along with their standard errors from the state accountability data. The input data to these models are the cutscores from Step 3 and the data prepared in Step 4. For each unit-subgroup-subject, we estimate two pooled HETOP models, one with 2009-2019 data and one with 2022-2024 data. For more details on the pooled HETOP model, see the SEDA 5.0 Technical Documentation and Shear and Reardon (2021).

As noted above, we use the unlinked reliability-adjusted cutscores in the pooled-HETOP mean estimation. The resulting district-subgroup-subject-grade mean and standard error estimates, $\hat{\mu}_{dygbh}^s$ and $se(\hat{\mu}_{dygbh}^s)$, are on a state standardized scale, and are not yet comparable across states, subjects or grades.

Step 6: Linking Mean Estimates.

We link the estimated means and their standard errors to a common scale using the NAEP data. Specifically, we use interpolated main state data from the NAEP, described under Step 5 State-All Student estimates. The linking equations are shown below (subgroup, subject, grade, year subscripts omitted for clarity).

$$\begin{aligned}\hat{\mu}_d^n &= \hat{\mu}_d^s \cdot \hat{\sigma}_s^n + \hat{\mu}_s^n \\ se(\hat{\mu}_d^n) &= \hat{\sigma}_s^n \cdot se(\hat{\mu}_d^s)\end{aligned}\tag{6.1}$$

The resulting $\hat{\mu}_{dygb}^n$ and $se(\hat{\mu}_{dygb}^n)$ are on the NAEP scale. However, the linked $se(\hat{\mu}_{dygb}^n)$ does not yet account for the uncertainty in NAEP. We create a second standard error $se'(\hat{\mu}_{dygb}^n)$ that incorporates the NAEP uncertainty, using the following formula (subgroup subscript omitted for clarity):

$$\begin{aligned}se^{adj}(\hat{\mu}_{dygb}^n) = & \sqrt{var(\hat{\mu}_{dygb}^n) + var(\hat{\mu}_{sygb}^n) - \left(\frac{1}{\hat{\sigma}_{sygb}^n}\right)^2 var(\hat{\mu}_{dygb}^n) var(\hat{\sigma}_{sygb}^n)} \\ & + var(\hat{\mu}_{sygb}^n)\end{aligned}\tag{6.2}$$

We report both standard errors in our data. The unadjusted standard error is appropriate for within-state comparisons, while the NAEP adjusted standard error is appropriate for cross-state comparisons.

Step 7: Creating Reporting Scales

Using interpolated national NAEP data,⁷ we standardize the NAEP-linked means and SEs to our four reporting scales: the Cohort Standardized (CS); the Year Standardized (YS); Grade Cohort Standardized (GCS); and the Grade Year Standardized (GYS) scales.

Cohort Standardized (CS) Scale: We standardize relative to the average of the four national cohorts that were in 4th grade in 2009, 2011, 2013, and 2015. This standardization is accomplished by subtracting the national grade-subject-specific mean and dividing by the national grade-subject-specific standard deviation for the average reference cohort. For each grade, year, and subject we calculate:

$$\begin{aligned}\mu_{N(avg)gb}^n &= \sum_{Y \in \{2005, 2007, 2009, 2011\}} \frac{1}{4} \hat{\mu}_{N(y=Y+g)gb}^n \\ \sigma_{N(avg)gb}^n &= \sum_{Y \in \{2005, 2007, 2009, 2011\}} \frac{1}{4} \hat{\sigma}_{N(y=Y+g)gb}^n\end{aligned}\quad (7.1)$$

In Equation (7.1), Y refers to the year in which the cohort was in the spring of kindergarten. For the 2009 4th grade cohort, this is equal to 2005 (or 2009 minus 4).

Then we standardize the means on the NAEP scale to the CS scale as follows (equations shown for districts, subgroup subscript omitted):

$$\begin{aligned}\hat{\mu}_{dygb}^{cs} &= \frac{(\hat{\mu}_{dygb}^n - \hat{\mu}_{N(avg)gb}^n)}{\sigma_{N(avg)gb}^n} \\ se(\hat{\mu}_{dygb}^{cs}) &= \frac{se(\hat{\mu}_{dygb}^n)}{\sigma_{N(avg)gb}^n}\end{aligned}\quad (7.2)$$

All means in this scale are interpretable as an effect size relative to the average of the four national cohorts that were in 4th grade in 2009, 2011, 2013, and 2015.

Year Standardized (YS) Scale: To create the YS scale, we standardize the NAEP-scaled estimates using the 2019 national average in each grade and subject. The equations to standardize to the YS scale are equivalent to those in 7.2 but using the scaling parameters are: $\hat{\mu}_{N(2019)gb}^n$ and $\hat{\sigma}_{N(2019)gb}^n$. In this scale, one unit is equivalent to a 2019 national standard deviation in the same subject and grade.

Grade Cohort Standardized (GCS): We approximate the average amount student test scores grow per grade on NAEP using the 4th and 8th grade estimates by subject for the average of the four national

⁷ We interpolate the national NAEP means and standard deviations using the same process as described in Step 5 for state NAEP means and standard deviations.

cohorts that were in 4th grade in 2009, 2011, 2013, and 2015. We calculate the amount the test scores changed between 4th and 8th grade as the average score in 8th grade minus the average score in 4th grade for each cohort; then average those across the four cohorts. Then, to get an estimate of per-grade differences, we divide that value by 4.

$$\hat{\gamma}_{N(avg)b} = \frac{\hat{\mu}_{N(avg)(8)b}^n - \hat{\mu}_{N(avg)(4)b}^n}{4} \quad (7.3)$$

We scale the data using these parameters, such that in the GCS scale each unit is interpretable as 1 grade level referenced to the four national cohorts that were in 4th grade in 2009, 2011, 2013, and 2015 (equations shown for districts, subgroup subscript omitted):

$$\begin{aligned} \hat{\mu}_{dygb}^{gcs} &= 4 + \frac{(\hat{\mu}_{dygb}^n - \hat{\mu}_{N(avg)(4)b}^n)}{\hat{\gamma}_{N(avg)b}} \\ se(\hat{\mu}_{dygb}^{gcs}) &= \frac{se(\hat{\mu}_{dygb}^n)}{\hat{\gamma}_{N(avg)b}} \end{aligned} \quad (7.4)$$

Grade Year Standardized (GYS): We approximate the average amount student test scores grow per grade on NAEP using the 4th and 8th grade estimates by subject in 2019. We calculate the amount the test scores changed between 4th and 8th grade as the average score in 8th grade in 2019 minus the average score in 4th grade in 2019. Then, to get an estimate of per-grade differences, we divide that value by 4 and denote it as $\hat{\gamma}_{N(2019)b}$. We scale the data using these parameters and equations similar to those in Equation 7.4, such that in the GYS scale each unit is interpretable as 1 grade level referenced to the 2019 national population.

Step 8: Constructing Annual Estimates

8.A. State All-Student Annual Estimates

We first use state NAEP data to construct state annual estimates. Specifically, we use data for grades 4 and 8 from each year, including the interpolated years constructed in Step 5 above (note, however, we do not use interpolated grade data).

We recover ordinary least squares (“OL”) annual estimates and variance-covariance (VCV) matrices for state-years via generalized least squares (GLS). We perform the following calculations using data for each state-year-subject-scale⁸ (subject subscript and scale superscript omitted for clarity):

$$\begin{aligned} \hat{\mathbf{B}}_{(y)s} &= (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}(\mathbf{X}'\mathbf{W}\mathbf{Y}) \\ \hat{\mathbf{V}}_{(y)s} &= (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1} \end{aligned} \quad (8A.1)$$

⁸ We also create a version combine data across subjects.

Where \mathbf{X} is the vector of grade 4 and 8 NAEP means, $\hat{\mu}_{(y)gs}$; and \mathbf{W} is a diagonal matrix of their variances, $var(\hat{\mu}_{(y)gs})$.

Using the same data, we also fit an HLM model by year-subject-subject-scale (subject subscript and scale superscript omitted for clarity) with state-grade observations, nested in states:

$$\begin{aligned}\hat{\mu}_{(y)gs} &= \beta_{(y)0s} + \beta_{(y)1s}(G - 5.5) + \epsilon_{(y)gs} \\ \beta_{(y)0s} &= \gamma_{(y)00} + r_{(y)0s} \\ \beta_{(y)1s} &= \gamma_{(y)10} + r_{(y)1s} \\ \epsilon_{(y)gs} &\sim (0, \zeta_{(y)gs}); \quad \mathbf{r}_{(y)s} \sim (0, \boldsymbol{\tau}_y)\end{aligned}\tag{8A.2}$$

From this, we get EB posterior state annual means and variances for all students: $\hat{\mathbf{B}}_{(y)s}^*$ and $\hat{\mathbf{V}}_{(y)s}^*$.

At the end of this step, we have both OL and EB state all student annual estimates ($\hat{\mathbf{B}}_{(y)s}$, $\hat{\mathbf{V}}_{(y)s}$, $\hat{\mathbf{B}}_{(y)s}^*$ and $\hat{\mathbf{V}}_{(y)s}^*$) for on all scales and their variances.

8.B. District All Student Annual Estimates

We then use district-subject-grade-year data, and the state annual estimates from Step 8A, to construct district annual estimates for all students. Note that we use the district data *without* the adjusted standard errors that account for the error in NAEP linking from Step 5 as input for these models. We will create a second adjusted standard error after model estimation.

We get OL estimates and VCV matrices for district-years via GLS. The process is identical to that for states (see Equation 8A.1) and provides the OL annual estimates and their unadjusted OL SEs: $\hat{\mathbf{B}}_{(y)d}$ and $\hat{\mathbf{V}}_{(y)d}$. We then construct an adjusted VCV matrix by adding the VCV matrix from the state-year model (created in step 8A, Equation 8A.1) to the district-year VCV matrix:

$$\hat{\mathbf{V}}_{(y)d}^{adj} = \hat{\mathbf{V}}_{(y)d} + \hat{\mathbf{V}}_{(y)s}\tag{8B.1}$$

To construct the EB annual estimates, we fit two HLM models. First, we fit a HLM model for each state-subject-scale with grades nested in years, nested in districts (subject subscript and scale superscripts omitted for clarity):

$$\hat{\mu}_{(s)gyd} = \beta_{(s)0yd} + \beta_{(s)1yd}(G - 5.5) + \epsilon_{(s)gyd} \quad (8B.2)$$

$$\beta_{(s)0yd} = \gamma_{(s)00d} + r_{(s)0yd}$$

$$\beta_{(s)1yd} = \gamma_{(s)10d} + r_{(s)1yd}$$

$$\gamma_{(s)00d} = \delta_{(s)000} + u_{(s)00d}$$

$$\gamma_{(s)01d} = \delta_{(s)010} + u_{(s)01d}$$

$$\gamma_{(s)10d} = \delta_{(s)100} + u_{(s)10d}$$

$$\epsilon_{(s)gyd} \sim (0, \zeta_{(s)gyd}); \quad \mathbf{r}_{(s)yd} \sim (0, \boldsymbol{\eta}_s); \quad \mathbf{u}_{(s)d} \sim (0, \boldsymbol{\tau}_s)$$

From this model, $\hat{\mathbf{u}}_{(s)d}$ is the average difference between the district parameters and the state s average parameters across years. We include $\hat{\mathbf{u}}_{(s)d}$ as a predictor in the second HLM model, estimated separately for each state-year-subject-scale (subject subscript and scale superscript omitted for clarity):

$$\hat{\mu}_{(sy)gd} = \beta_{(sy)0d} + \beta_{(sy)1d}(G - 5.5) + \epsilon_{(sy)gd} \quad (8B.3)$$

$$\beta_{(sy)0d} = \gamma_{(sy)00} + \gamma_{(sy)01}(\hat{u}_{(s)00d}) + r_{(sy)0d}$$

$$\beta_{(sy)1d} = \gamma_{(sy)10} + \gamma_{(sy)11}(\hat{u}_{(s)10d}) + r_{(sy)1d}$$

$$\epsilon_{(sy)gd} \sim (0, \zeta_{(sy)gd}); \quad \mathbf{r}_{(sy)d} \sim (0, \boldsymbol{\eta}_{sy})$$

From this model, we get the EB posterior means and variances: $\hat{\mathbf{B}}_{(sy)d}^*$ and $\hat{\mathbf{V}}_{(sy)d}^*$. However, we want to adjust the posterior means to be centered at the state EB posterior mean to account for shrinkage of the state estimate to the national mean. To do this, we subtract the state OL estimate and add the state EB estimate. We also construct an adjusted posterior variance matrix by adding the posterior VCV matrix from the state-year model (created in Step 8A, Equation 8A.2) to the district-year posterior VCV matrix.

$$\hat{\mathbf{B}}_{(y)d}^{*adj} = (\hat{\mathbf{B}}_{(sy)d}^* - \hat{\mathbf{B}}_{(y)s}) + (\hat{\mathbf{B}}_{(y)s}^*) \quad (8B.4)$$

$$\hat{\mathbf{V}}_{(y)d}^* = \hat{\mathbf{V}}_{(sy)d}^*$$

$$\hat{\mathbf{V}}_{(y)d}^{*adj} = \hat{\mathbf{V}}_{(sy)d}^* + \hat{\mathbf{V}}_{(y)s}^*$$

8.C. State and District Subgroup Estimates

To construct state and district annual estimates for each subgroup, denoted h , we use the data from the state assessments both from subgroups and from the all-student group. The estimation process is largely identical for the construction of both state and district subgroup estimates; we describe the

process for states below and note any differences for the district estimation. For clarity, we show the subgroup as a superscript in the below equations and omit the scale superscript.

We first get OL estimates and VCV matrices for state subgroups via GLS:

$$\begin{aligned}\hat{\mathbf{B}}_{(y)s}^h &= (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}(\mathbf{X}'\mathbf{W}\mathbf{Y}) \\ \hat{\mathbf{V}}_{(y)s}^h &= (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\end{aligned}\tag{8C.1}$$

We construct an adjusted OL variance matrix, $\hat{\mathbf{V}}_{(y)s}^{hadj}$, using the same process as shown in equation 8B.1.

To get EB estimates, we first compute the difference in mean scores between group h and the *all* mean in each state-grade-year (where p_{gys}^h is the proportion of group h in the state-grade-year):

$$\begin{aligned}\Delta\hat{\mu}_{gys}^h &= \hat{\mu}_{gys}^h - \hat{\mu}_{gys}^{all} \\ \zeta_{gys} &= \left(\frac{1 - p_{gys}^h}{p_{gys}^h}\right) var(\hat{Y}_{gys}^{all})\end{aligned}\tag{8C.2}$$

We will use these differences as the outcome in our HLM models, such that the resulting estimates will be estimates produced will also be for the *differences* between the subgroup and the all group.

We fit two HLM models. First, we fit an HLM model with grades, nested in years, nested in states (data for all states are included in one model):

$$\begin{aligned}\Delta\hat{\mu}_{gys}^h &= \beta_{0ys}(1 - p_{gys}^h) + \beta_{1ys}(G - 5.5)(1 - p_{gys}^h) + \epsilon_{gys} \\ \beta_{0ys} &= \gamma_{00s} + r_{0ys} \\ \beta_{1ys} &= \gamma_{10s} + r_{1ys} \\ \gamma_{00s} &= \delta_{000} + u_{00s} \\ \gamma_{10s} &= \delta_{100} + u_{10s} \\ \epsilon_{gys} &\sim (0, \zeta_{gys}); \quad \mathbf{r}_{ys} \sim (0, \boldsymbol{\eta}); \quad \mathbf{u}_s \sim (0, \boldsymbol{\tau})\end{aligned}\tag{8C.3}$$

From this model, $\hat{\mathbf{u}}_s$ is the average difference between the state gap parameters and the national gap parameters, across years. (Note: For districts, we estimate the above model separately for each state. In the district model, $\hat{\mathbf{u}}_d$ is the average difference between the district gap parameters and the state gap parameters.)

We then use $\hat{\mathbf{u}}_s$ to predict the value of the state parameters in each year in a second HLM model (estimated separately for each year):

$$\Delta\hat{\mu}_{(y)gs}^h = \beta_{(y)0s}(1 - p_{(y)gs}^h) + \beta_{(y)1s}(G - 5.5)(1 - p_{(y)gs}^h) + \epsilon_{(y)gs} \quad (8C.4)$$

$$\beta_{(y)0s} = \gamma_{(y)00} + \gamma_{(y)01}(\hat{u}_{00s}) + r_{(y)0s}$$

$$\beta_{(y)1s} = \gamma_{(y)10} + \gamma_{(y)11}(\hat{u}_{10s}) + r_{(y)1s}$$

$$\epsilon_{(y)gs} \sim (0, \zeta_{(y)gs}); \quad \mathbf{r}_s \sim (0, \boldsymbol{\eta}_y)$$

From this model, we get EB estimates of the difference between the subgroup h and the all group, $\hat{\mathbf{B}}_{(y)s}^{\Delta h*}$ and $\hat{\mathbf{V}}_{(y)s}^{\Delta h*}$. To get the state annual subgroup estimates, we need to add the resulting EB estimates from the model above to those for all students:

$$\hat{\mathbf{B}}_{(y)s}^{h*} = \hat{\mathbf{B}}_{(y)s}^{\Delta h*}(1 - \bar{p}_{(y)s}^h) + \hat{\mathbf{B}}_{(y)s}^{all*} \quad (8C.5)$$

$$\hat{\mathbf{V}}_{(y)s}^{h*} = \hat{\mathbf{V}}_{(y)s}^{\Delta h*}(1 - \bar{p}_{(y)s}^h)^2 + \hat{\mathbf{V}}_{(y)s}^{all*}$$

$$\hat{\mathbf{V}}_{(y)s}^{h*adj} = \hat{\mathbf{V}}_{(y)s}^{\Delta h*}(1 - \bar{p}_{(y)s}^h)^2 + \hat{\mathbf{V}}_{(y)s}^*$$

Step 9: Suppressing and Flagging Data for Release

Our goal is to ensure that the data we release is useful for various education stakeholders. We take caution to not report data that is unreliable and to flag estimates that require additional information for interpretation.

Long Form Files. Our agreement with the US Department of Education requires (1) that all reported unit-subgroup-subject-grade-year estimates reflect at least 20 unique students; and (2) that a small amount of random noise is added to each estimate in proportion to the sampling variance of the respective estimate for any estimates based on *EDFacts* (estimates from 2009 to 2019). The added noise is roughly equivalent to randomly removing one student's score from each unit-subgroup-subject-grade-year estimate. These measures are taken to ensure that the raw counts of students in each proficiency category cannot be recovered from published estimates. The random error added to each unit-subgroup estimate is drawn from a normal distribution $\mathcal{N}(0, (1/n) * \hat{\omega}^2)$ where $\hat{\omega}^2$ is the squared estimated standard error of the estimate and n is the number of student assessment outcomes to which the estimate applies. The SEs of the mean are adjusted to account for the additional error. We apply the cell size restriction, but do not add noise to estimates based on the public state data (estimates from 2022 to 2024).

For all years, we remove any imprecise individual estimates where the CS scale standard error is greater than 1. Any individual estimate with such a large standard error is too imprecise to use in analysis. We also remove all estimates associated with units that are based on more than 20% alternate assessments across the grades and years in the *EDFacts* data. We suppress all subgroup estimates if the mean is missing for the “all” subgroup. Finally, we suppress estimates whenever the mean, standard deviation, or standard error of either is missing.

Annual Files. For all annual files, our agreement with the US Department of Education requires that all reported estimates (1) reflect at least 20 unique students; and (2) are pooled across at least two subject-grades for all estimates based on *EDFacts* data. We do not require these for annual estimates based on 2022 to 2024 public data.

We additionally suppress unreliable estimates. To get reliability estimates, we estimate a HLM model⁹ in each year using the data for all students and all districts in the country. From this model, we use τ_y and the reliabilities of $\mathbf{B}_{(y)d}$. Use τ_y to determine suppression based on imprecision (suppress β_{y0d} and β_{y1d} if the $\frac{\tau_{y00}}{\tau_{y00} + V_{yd00}} < 0.7$, or equivalently, if $se(\beta_{y0d}) < \sqrt{\frac{3}{7}\tau_{y00}}$. If we are going to report β_{y1d} – the annual grade slopes—then we also need to suppress β_{y1d} if $se(\beta_{y1d}) < \sqrt{\frac{3}{7}\tau_{y11}}$. We suppress estimates for the all student group and subgroups using the reliabilities estimated from this model.

Data flags.

In the downloadable data, we include three flags: (1) flag_estasmt, (2) flag_rel33, and (3) flag_1924. flag_estasmt is included in all file types (“long”, “annualsub” and “annual”) and indicates whether we estimated the total number of students tested (= 1 if the number of assessments, tot_asmt, was estimated) for the row. flag_rel33 is included in the “annualsub” and “annual” files and indicates whether the estimate was deemed reliable (= 1 if reliable). flag_1924 is included in the “annualsub” and “annual” files and indicates whether the unit-subgroup or unit-subgroup-subject has an estimate data for 2019, 2022, and 2024.

⁹ The HLM model is:

$$\begin{aligned}\hat{\mu}_{(y)gd} &= \beta_{(y)0d} + \beta_{(y)1d}(G - 5.5) + \epsilon_{(y)gd} \\ \beta_{(y)0d} &= \gamma_{(y)00} + r_{(y)0d} \\ \beta_{(y)1d} &= \gamma_{(y)10} + r_{(y)1d} \\ \epsilon_{(y)gd} &\sim (0, \zeta_{(y)gd}); \quad \mathbf{r}_{(y)d} \sim (0, \tau_y)\end{aligned}$$

On our website, we flag districts in the data where there were large changes in the overall enrollment and/or in the racial composition using grade 3-8 CCD enrollment data by district-subgroup from fall 2019 and fall 2023. We identified districts as having large changes in overall enrollment if the proportional change in grade 3-8 CCD enrollment was greater than .20 (20%), calculated as:

$$\frac{|g38enroll_{2022} - g38enroll_{2019}|}{\min(g38enroll_{2022}, g38enroll_{2019})} > .20$$

We opted to flag these places to indicate that changes in achievement should be interpreted with caution given the change in student population.

I.E. Data Quality and Validation Checks

Inferences regarding changes in the estimated test scores from 2019 to 2024 hinge on the comparability of the data over time. There are a few potential threats to these inferences:

Data discrepancies. Because state reported proficiency data are the source data for *EDFacts*, the data reported in the two sources should be equivalent (save for differences in data suppression). However, as part of the *EDFacts* data collection process, state proficiency data are vetted and cleaned. As such, it is possible that the 2022-2024 state data are of lower or different quality than the 2019 *EDFacts* data. Additionally, there may be differences in how the data are reported, for example, whether alternate assessments are reported in the count data for each district.

To better understand any potential discrepancies in the data, we cleaned the 2019 state reported data using the same rules (described above) as the 2022-2024 state reported data. We then compared the count data and estimates produced from both sources. Differences in estimated means are associated with differences in the underlying count data at the state and/or district levels (i.e., the two sources reported different proportions of students scoring at the same proficiency level). On average, these differences in the estimated means were small (.07 grade levels). Only in a small percentage of cases (6.6%) did estimates differ by more than .2 grade levels. More than three-quarters of cases with differences larger than .2 grade levels are in district-subject-grades with fewer than 100 test-takers; only 3% are in cases with more than 500. Thus, while there are differences in the data, they would impact the estimates we report in limited ways for relatively few test-takers.

Notably, as a result of this analysis, we determined that the data reported in *EDFacts* for Arkansas RLA is not comparable to the data reported by the state in either Reading or English. As such RLA data for Arkansas was removed from website and data files.

NAEP Linking. We replicated a subset of the analyses from Reardon, Kalogrides, and Ho (2021) to demonstrate that the NAEP linking continues to perform well in 2022 and 2024.

Comparison to percent proficient data. As a face validity check of the data, for each state-subject we correlated our estimated changes in means (pooled over grades) with changes in the probit transformed reported percent proficient (pooled over grades). Correlations suggest that our estimates tell a story that is largely consistent with that from the reported percent proficient.

I.F. Version Changes

Multiple improvements have been made to the data cleaning and estimation process since the SEDA 2024 release. The key changes are detailed here:

- Change to use Zelma source data, including district participation.
- The integration of the 2024 state assessment data.
- New annual estimation models and shrinkage approach.

Because of these changes, the sample of districts and the 2022 and 2023 estimates in SEDA 2024 may not match those from prior versions.

II. Covariates

II.A. Overview of Covariate Files

SEDA 2024 includes estimates of socioeconomic, demographic, and segregation characteristics of administrative districts and states. We release two data files, shown in **Table 4** [Table 4. Covariate Data Files](#), which report data for each unit by year. For information about the construction

II.B. Source Data

The measures we report come from two primary sources:

- The Common Core of Data (CCD). The CCD is an annual survey of all public elementary and secondary schools and school districts in the United States. The CCD data include basic descriptive information on schools and school districts, including demographic characteristics.¹⁰ We use data from 2008-09 to 2023-24 and aggregate school level CCD data to larger units (e.g., administrative districts, counties).

¹⁰ The CCD is available for download from the NCES website: <https://nces.ed.gov/ccd/>.

- The American Community Survey (ACS). We obtain detailed tables from the National Historical Geographic Information System (NHGIS) web portal,¹¹ which include data on the demographic and socioeconomic characteristics of individuals and households residing in each unit. For these measures, we report data only from 2009 to 2019.

II.C. Construction of Covariate Files

For information about the construction of our covariate files, we refer interested readers to the SEDA 5.0 Technical Documentation.

References

- Raudenbush, S.W., & Congdon, R.T. (2021). *HLM 8: Hierarchical linear and nonlinear modeling*. Chapel Hill, NC: Scientific Software International, Inc.
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<https://doi.org/10.3102/1076998616666279>
- Reardon, S. F., Kalogrides, D., & Ho A. D. (2021). Validation methods for aggregate-level test scale linking: A case study mapping school district test score distributions to a common scale. *Journal of Educational and Behavioral Statistics*, 46(2), 138–167.<http://doi.org/10.3102/1076998619874089>
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- State Assessments in Reading/Language Arts and Mathematics- School Year 2018-19 EDFacts Data Documentation*, U.S. Department of Education, Washington, DC: EDFacts. Retrieved 04/24/2023 from <http://www.ed.gov/edfacts>.

¹¹ The ACS data is available for download from the IPUMS-NHGIS website at: <https://www.nhgis.org/>. Full citation: Steven Manson, Jonathan Schroeder, David Van Riper, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 14.0 [Database]. Minneapolis, MN: IPUMS. 2019. <http://doi.org/10.18128/D050.V14.0>

Tables & Figures

Table 1. Test Score Files

File Name	Form	Metric	Unit		Disaggregated by			Subgroups			
			Administrative District	State	Year	Grade	Subject	Means			
								All	Race	Gender	ECD
seda_admindist_annualsub_cs_2024.1	Annual by Subject	CS	X		X		X	X	X	X	X
seda_admindist_annualsub_gcs_2024.1	Annual by Subject	GCS	X		X		X	X	X	X	X
seda_admindist_annualsub_gys_2024.1	Annual by Subject	GYS	X		X		X	X	X	X	X
seda_admindist_annualsub_ys_2024.1	Annual by Subject	YS	X		X		X	X	X	X	X
seda_admindist_annual_cs_2024.1	Annual	CS	X		X			X	X	X	X
seda_admindist_annual_gcs_2024.1	Annual	GCS	X		X			X	X	X	X
seda_admindist_annual_gys_2024.1	Annual	GYS	X		X			X	X	X	X
seda_admindist_annual_ys_2024.1	Annual	YS	X		X			X	X	X	X
seda_admindist_long_cs_2024.1	Long	CS	X		X	X	X	X	X	X	X
seda_admindist_long_gcs_2024.1	Long	GCS	X		X	X	X	X	X	X	X
seda_admindist_long_gys_2024.1	Long	GYS	X		X	X	X	X	X	X	X
seda_admindist_long_ys_2024.1	Long	YS	X		X	X	X	X	X	X	X
seda_state_annualsub_cs_2024.1	Annual by Subject	CS		X	X		X	X	X	X	X
seda_state_annualsub_gcs_2024.1	Annual by Subject	GCS		X	X		X	X	X	X	X
seda_state_annualsub_gys_2024.1	Annual by Subject	GYS		X	X		X	X	X	X	X
seda_state_annualsub_ys_2024.1	Annual by Subject	YS		X	X		X	X	X	X	X
seda_state_annual_cs_2024.1	Annual	CS		X	X			X	X	X	X
seda_state_annual_gcs_2024.1	Annual	GCS		X	X			X	X	X	X
seda_state_annual_gys_2024.1	Annual	GYS		X	X			X	X	X	X
seda_state_annual_ys_2024.1	Annual	YS		X	X			X	X	X	X
seda_state_long_cs_2024.1	Long	CS		X	X	X	X	X	X	X	X
seda_state_long_gcs_2024.1	Long	GCS		X	X	X	X	X	X	X	X
seda_state_long_gys_2024.1	Long	GYS		X	X	X	X	X	X	X	X
seda_state_long_ys_2024.1	Long	YS		X	X	X	X	X	X	X	X

Table 2. State Accountability Data Overview, 2022-2024

State	Subgroups reported	Estimated counts (% of districts)	Partial suppression
AL	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	95.3	Y
AK	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
AR	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	Y
AZ	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	Y
CA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
CO	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
CT	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	6.08	Y
DE	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
DC	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
FL	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
GA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0.87	N
HI	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	Y
ID	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
IL	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	N
IN	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
IA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N

KS	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	Y
KY	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	N
LA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	79.71	Y
MA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
MD	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
MI	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
MN	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
MO	All, Asian, Black, ECD, Hispanic, Not-ECD, White students	0	Y
MS	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0.69	Y
MT	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	20.32	Y
NC	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
ND	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	100	Y
NE	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	99.58	Y
NH	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	98.2	Y
NJ	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	85.19	N
NY	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
NV	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
OH	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y

OK	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	95.19	Y
OR	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
PA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
RI	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
SC	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
SD	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
TN	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
TX	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
UT	All, Asian, Black, ECD, Hispanic, White students	100	Y
VA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	Y
WA	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	76.07	Y
WI	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	0	N
WV	All, Asian, Black, ECD, Female, Hispanic, Male, White students	100	N
WY	All, Asian, Black, ECD, Female, Hispanic, Male, Not-ECD, White students	98	Y

Table 3a. Availability of SEDA 2024 Estimates by State-Subject-Year-Grade

[illegible]

[illegible]

[illegible]

[illegible]

Table 3b. Reason for Unavailability of SEDA 2024 Estimates by State-Subject-Year-Grade

[illegible]

[illegible]

North Dakota																		
Math								4 4	2 2 2									
RLA								4 4	2 2 2 2									
Ohio																		
Math								3 3 3 3 3 3	3	3 3	3 3	3 3	3 3	3 3	1	1 1	1 1	
RLA								3 3 3 3 3 3										
Oklahoma																		
Math				3				3										
RLA																		
Oregon																		
Math								2 2 2 2 2				2		2				
RLA								2 2 2 2										
Pennsylvania																		
Math															1	1	1	
RLA															1	1	1	
Rhode Island																		
Math										2 2 2								
RLA										2 2 2								
South Dakota																		
Math										2 2 2 2 2 2								
RLA										2 2 2 2 2 2								
Tennessee																		
Math		3		3		3		3		3		3 5 5 5 5 5 2	3	3	3	1	1	1
RLA												5 5 5 5 5 2						
Texas																		
Math							3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	1 1	1 1	1 1
RLA	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3	3 3			1	
Utah																		
Math		3		3		3		3				2	2 2 2	2 2 2				
RLA													2 2	2 2 2				
Vermont																		
Math								2 2 2 2 2 2						1 1 1 1 1 1 1 1 1 1 1 1				
RLA								2 2 2 2 2 2						1 1 1 1 1 1 1 1 1 1 1 1				
Virginia																		
Math	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	3 3 3 3	1 1 1 1 1 1 1 1	3 3 3 3	1 1 1 1	1 1 1 1	1 1 1 1	
RLA																		

Washington									
Math							2	2	2
RLA							2	2	2
West Virginia									
Math							2	2	2
RLA									
Wyoming									
Math	1	1	1	1	1	1			
RLA	1	1	1	1	1	1			

Note. 1 = Not available in *EDFacts*; 2 = <94% or >105% participation; 3 = Different tests; 4 = Different counts; 5 = Insufficient data.

Table 4. Covariate Data Files

File Name	Form	Disaggregated by		
		Unit	Year	Grade
seda_cov_admindist_annual_2024.1	Annual	X	X	
seda_cov_state_annual_2024.1	Annual	X	X	