Stanford Education Data Archive

Technical Documentation

Version 5.0

March 2024

Erin M. Fahle, Stanford University

jim saliba, Stanford University

Demetra Kalogrides, Stanford University

Benjamin R. Shear, University of Colorado Boulder

Sean F. Reardon, Stanford University

Andrew D. Ho, Harvard University

Suggested citation:
Fahle, E. M., saliba, j., Kalogrides, D., Shear, B. R., Reardon, S. F., & Ho, A. D. (2024). Stanford Education Data Archive: Technical Documentation (Version 5.0). Retrieved from https://purl.stanford.edu/cs829jn7849.

Contents

I. What is SEDA?

The Stanford Education Data Archive (SEDA) is part of the Educational Opportunity Project at Stanford University (https:\\edopportunity.org), an initiative aimed at harnessing data to help scholars, policymakers, educators, and parents learn how to improve educational opportunities for all children. SEDA includes a range of detailed data on educational conditions, contexts, and outcomes in schools, school districts, counties, commuting zones, metropolitan statistical areas, and states across the United States. Available measures differ by aggregation; see Sections I.A. and I.B. for a complete list of files and data.

By making the data files available to the public, we hope that anyone who is interested can obtain detailed information about U.S. schools, communities, and student success. We hope that researchers will use these data to generate evidence about how educational policies and contexts can increase educational opportunity.

The construction of SEDA has been supported by grants from the Bill and Melinda Gates Foundation, the Institute of Education Sciences, the Spencer Foundation, the William T. Grant Foundation, the Overdeck Family Foundation, and by a visiting scholar fellowship from the Russell Sage Foundation. Some of the data used in constructing the SEDA files were provided by the National Center for Education Statistics (NCES). The findings and opinions expressed herein are those of the authors alone; they do not represent the views of the U.S. Department of Education, NCES, or any of the funding agencies.

I.A. Overview of Test Score Data Files

SEDA 5.0 contains test score data files for schools, geographic school districts, administrative school districts, counties, commuting zones, metropolitan statistical areas, 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 2018-19 school years. The measures contained in the data files are detailed below.

School Files. We release two school-level test score data files (pooled over subjects, grades, and years), one for each metric: the cohort standardized (CS) scale and the grade cohort standardized (GCS) scale. In each file there are variables corresponding to the average test score in the middle grade of the data, the average "learning rate" across grades (grade slope), the average "trend" in test scores across cohorts (cohort slope), and the average difference between math and RLA test scores (math slope). Each measure is included along with its respective standard error. School estimates are only reported for all students; no estimates are provided by demographic subgroup.

Geographic School District, Administrative School District, County, Commuting Zone, Metropolitan Statistical Area, and State Files. We release thirty-six test score files corresponding to the six units (geographic school districts, administrative school districts, counties, metropolitan areas, commuting zones, and states) by two scales (CS and GCS) by three pooling levels (long, pooled by subject, and pooled overall). "Long" files contain estimates for each grade and year separately; "pooled by subject" (or poolsub) files contain estimates that are averaged across grades and years within subjects; and "pooled overall" (or pool) files contain estimates that are averaged across grades, years, and subjects. The long files contain grade-year-subject test score means and their respective standard errors. The poolsub files contain the average test score mean in math and in RLA (averaged across grades and years), the average "learning rate" across grades in math and in RLA, and the average "trend" in test scores across cohorts in math and in RLA, along with their standard errors. The pooled overall files contain the average test score mean (averaged across grades, years, and subjects), the average "learning rate" across grades, the average "trend" in test scores across cohorts, and the average difference between math and RLA test scores, along with their standard errors. In all files, estimates are reported for all students and by demographic subgroups.

The Achievement Data Construction section of the documentation describes more detail about the construction of the test score estimates. Table 1 lists the files and file structures. Lists of variables can be found in the codebooks that accompany this documentation.

I.B. Covariate Data

SEDA 5.0 also includes estimates of socioeconomic, demographic, and segregation characteristics of schools, geographic districts, administrative districts, counties, metropolitan areas, and states. The measures we report come from three 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.[1] We aggregate school level CCD data to larger units (e.g., geographic districts, counties).[2]
- The Civil Rights Data Collection (CRDC). The CRDC includes data about school demographics, teacher experience, school expenditures, high school course enrollments as well as other information not used here.[3]
- The American Community Survey (ACS). We obtain detailed tables from the National Historical Geographic Information System (NHGIS) web portal,[4] which include data on the demographic and socioeconomic characteristics of individuals and households residing in each unit. The measures from the ACS are not available at the school level.

School Files. We provide two covariate data files for schools; one includes an observation for each school in each year and the other reports a single record for each school that is the average across years.

Geographic School District, Administrative School District, County, Commuting Zone, Metropolitan Statistical Area, and State Files. We release fifteen covariate data files for all other units (three per unit). The three covariate files we construct for each unit contain the same

---

[1] The CCD is available for download from the NCES website: https://nces.ed.gov/ccd/.

[2] The exception is the finance data (total instructional expenditures and per pupil expenditures) which are only available at the district level. These measures are aggregated from the district level to the county and metropolitan area levels and are not available at the school level.

[3] The CRDC data is available for download at: https://ocrdata.ed.gov/.

[4] 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

variables but at different aggregations: separately for each grade and year, averaged across grades (providing a single value per unit per year), or averaged across grades and years (providing a single value per unit).

The Covariate Data Construction section of the documentation describes more detail about the construction of these data files and the computation of derived variables. Table 2 lists the names and file structures of the covariate data files. Lists of variables can be found in the codebooks that accompanies this documentation.

I.C. Data Use Agreement

Prior to downloading the data, users must sign the data use agreement, shown below.

You agree not to use the data sets for commercial advantage, or in the course of for-profit activities. Commercial entities wishing to use this Service should contact Stanford University's Office of Technology Licensing (info@otlmail.stanford.edu).

You agree that you will not use these data to identify or to otherwise infringe the privacy or confidentiality rights of individuals.

THE DATA SETS ARE PROVIDED "AS IS" AND STANFORD MAKES NO REPRESENTATIONS AND EXTENDS NO WARRANTIES OF ANY KIND, EXPRESS OR IMPLIED. STANFORD SHALL NOT BE LIABLE FOR ANY CLAIMS OR DAMAGES WITH RESPECT TO ANY LOSS OR OTHER CLAIM BY YOU OR ANY THIRD PARTY ON ACCOUNT OF, OR ARISING FROM THE USE OF THE DATA SETS.

You agree that this Agreement and any dispute arising under it is governed by the laws of the State of California of the United States of America, applicable to agreements negotiated, executed, and performed within California.

You agree to acknowledge the Stanford Education Data Archive as the source of these data. In publications, please cite the data as:

Reardon, S. F., Ho, A. D., Shear, B. R., Fahle, E. M., Kalogrides, D., saliba, j. (2024). Stanford Education Data Archive (Version 5.0). Retrieved from https://purl.stanford.edu/cs829jn7849.

Subject to your compliance with the terms and conditions set forth in this Agreement, Stanford grants you a revocable, non-exclusive, non-transferable right to access and make use of the Data Sets.

II. Achievement Data Construction

II.A. Source Data

The SEDA 5.0 test scores estimates are constructed using data from the ED*Facts* data system housed by the U.S. Department of Education. The ED*Facts* 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.[5] States have the flexibility to select or design a test of their choice 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. Typically, states select 2 to 5 performance levels, where one or more levels represent "proficient" grade-level achievement.

To ED*Facts*, states report the number of students in each school, subgroup, subject, grade, and year scoring at each of their defined performance levels; <u>*no individual student-level data is reported*</u>.[6] ED*Facts* currently contains these school assessment outcomes for ten consecutive school years from the 2008-09 school year to the 2018-19 school year in grades 3 to 8 in RLA and math. The student subgroups include race/ethnicity, gender, and socioeconomic disadvantage, among others not used in SEDA 5.0.

The raw ED*Facts* data used in SEDA include no suppressed cells, nor do they have a minimum cell size for reporting. Each row of data corresponds to a school-subgroup-subject-grade-year cell. Table 3 illustrates the structure of the raw data from ED*Facts* prior to use in constructing SEDA 5.0.

[5] Federal law also requires states to report data for one high school grade; however, that data is not currently used in SEDA.

[6] In recent years (2013-2019), the data is further broken out by the assessment type administered to students: regular assessments, regular assessments with accommodations, and alternate assessments with grade-level standards, modified standards and alternate standards. However, in 2009-2012, ED*Facts* does not distinguish students taking regular from alternate assessments. Therefore, for consistency in all years, we use all performance data reported in ED*Facts*, including results of students taking both regular and alternate assessments.

II.B. 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 National Center for Education Statistics (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.

Commuting Zone: Regions defined by the geographic boundaries of a local economy. We use the ERS 2010 boundary definitions (https://sites.psu.edu/psucz/data/) which are the most recent commuting zone definitions.

Geographic School District: The aggregate of all public schools in SEDA (except for special education[7] and virtual[8] schools) that are physically located within a geographically defined public Elementary or Unified school district. We use the 2019 Elementary and Unified School District Boundaries (https://nces.ed.gov/programs/edge/Geographic/DistrictBoundaries) to define these districts. Note that there are some districts in SEDA that are not geographically defined that are included in our analysis. In this document, the terms "geographic district," "geographic school district," and "geographically-defined school district" are used interchangeably.

Group: The term "group" refers to a unit-subgroup. For schools, the only available subgroup is all students. For geographic school districts, administrative school districts, counties, commuting zones, metropolitan areas, and states, data for other subgroups are available when estimates are sufficiently precise.

Metropolitan Statistical Area: A county or group of counties with a population exceeding 50,000 and encompassing an urban area, combined with any surrounding counties with strong commuting ties to the urban area.[9] The U.S. Census Bureau revises the metropolitan statistical area definitions after each decennial census. We use the 2013 U.S. Census Bureau definitions,

[7] As defined by school type in the CCD Public Elementary/Secondary School Universe Survey Data.
[8] As defined by virtual text in the CCD Public Elementary/Secondary School Universe Survey Data.
[9] https://www.census.gov/programs-surveys/metro-micro/about/glossary.html

which are the definitions based on the 2010 census.[10] We make one modification to the definitions. The Census defines very large metropolitan areas as Consolidated Metropolitan Statistical Areas (CMSAS); each CMSA is subdivided into Metropolitan Area Divisions. We treat each division as a separate metropolitan area for analysis purposes, as the CMSAs are generally quite large.

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

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 (nonECD) 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 (nonECD).

Unit: The term "unit" refers to the aggregation or the geographic level of the data. This may be a school, geographic school district, administrative school district, county, commuting zone, metropolitan area, or state.

II.C. Construction Overview

The construction process produces mean test score estimates for schools, geographic districts, administrative districts, counties, metropolitan areas, commuting zones, and states on two nationally comparable scales in a series of nine steps, outlined in Figure 1. We provide a brief conceptual description of each step here and the full technical details about each step in Section II.E.

[10] https://www.census.gov/programs-surveys/metro-micro/geographies/geographic-reference-files.2013.html

Step 1: Creating the Crosswalk. This step links each public school to a unique stable school, geographic school district, administrative school district, county, commuting zone, metropolitan area, and state.

Step 2: Data Cleaning. This step removes data not used in SEDA 5.0.

Step 3: Estimating and Linking Cutscores. This step uses Heteroskedastic Ordered Probit (HETOP) models to estimate the state-grade-subject-year cutscores, then links the estimated cutscores to the NAEP scale and standardizes the linked cutscores to the Cohort Standardized (CS) scale. The resulting cutscores are comparable across states and years.

Step 4: Selecting Data for Mean Estimation. This step selects data for *unit-subgroup-subject-grade-year* cases that will be used in estimation. We exclude cases with low participation in the assessment or high percentages of students taking alternate assessments. We also exclude cases for which we have insufficient data to produce an estimate.

Step 5: Estimating Means. This step uses the pooled HETOP model to estimate school, geographic district, administrative district, county, commuting zone, metropolitan area, and state subgroup-subject-grade-year means and standard deviations, along with their standard errors, based on the cutscores from Step 3 and the data prepared in Step 4.

Step 6: Creating Additional Reporting Scales. This step creates Grade Cohort Standardized (GCS) estimates for all units, such that each unit is interpreted as 1 grade level. From this point onward, we have two scales of data for all units: CS and GCS. Subsequent steps are equivalent for both scales unless otherwise noted.

Step 7: Calculating Achievement Gaps. This step estimates White-Black, White-Hispanic, White-Asian, White-Native American, male-female, and nonECD-ECD achievement gaps for geographic districts, administrative districts, counties, metropolitan areas, commuting zones, and states in each subject-grade-year where there is sufficient data.

Step 8: Pooling Mean and Gap Estimates. This step estimates the average achievement, learning rate, and trend in test scores by subject and overall for each unit and scale. From this point onward, we have three types of data for geographic districts, administrative districts, counties, metropolitan areas, commuting zones, and states: long (by grade, year, or subject), pooled by subject (poolsub; pooled over grades and years by subject), and pooled overall (pool; pooled over grades, years, and subjects). For schools, we only report the pooled overall (pool) estimates.

Step 9: Suppressing Data for Release. For both long and pooled files for all units and scales, ethis step suppresses estimates that are too imprecise to be useful or do not reflect the performance of at least 20 unique students. For estimates reported in the long files, this step adds a small amount of random noise to meet the reporting requirements of the US Department of Education.

II.D. Notation

In the remainder of the documentation, we use the following mathematical notation:

- Mean estimates are denoted by $\hat{\mu}$ and standard deviation estimates by $\hat{\sigma}$.
- The cutscore estimates are denoted as $\hat{c}_1, \ldots, \hat{c}_K$. There are K total cutscores in each state-subject-grade-year.
- A subscript indicates the aggregation of the estimate. We use the following subscripts:
    - u = unit (generic)
    - n = school
    - d = geographic school district
    - a = administrative school district
    - c = county
    - z = commuting zone
    - m = metropolitan area
    - f = state
  - r = subgroup
    - all = all students
    - asn = Asian
    - blk = Black
    - hsp = Hispanic
    - nam = Native American
    - wht = White
    - fem = female

mal = male
ecd = economically disadvantaged
nec = not economically disadvantaged
wag = White-Asian gap
wbg = White-Black gap
whg = White-Hispanic gap
wng = White-Native American gap
mfg = male-female gap
neg =not economically disadvantaged-economically disadvantaged gap

y = year
b = subject
g = grade

- A superscript indicates the scale of the estimate. The metric is generically designated as x. There are four scales. The first two scales are only used in construction. The latter two scales are reported:

  $state$ = state-standardized metric
  $naep$ = NAEP test score scale metric
  cs = cohort scale metric
  gcs = grade within cohort scale metric

II.E. Detailed Construction Overview

Step 1. Creating the Crosswalk

The primary purpose of the crosswalk is to create stable school identifiers and assign schools to larger units such as geographic school districts, administrative school districts, counties, metropolitan areas, commuting zones, and states. 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) as the basis for the crosswalk.

Stable School IDs. Since we want to be able to track schools as they change districts (district changes could be due to districts splitting, merging or some other administrative change), we create stable school IDs using the CCD's *Longitudinal ID Crosswalks*. According to the CCD documentation, "Schools are uniquely identified in CCD by the 12-digit variable **ncessch**. This variable is a combination of the state code (the first two digits or FIPST), the Local Education Agency (LEA) ID (the first seven digits or **leaid**) and the last five digits (**schid**). It was always intended that the **schid** should be unique within the state so that a school could be tracked from year-to-year even if a re-organization caused it to change LEAs. However, a system error created some duplicate **schid**s within some states."[11]

Because some schools changed school IDs during the 2008-09 to 2018-19 time period, we use the CCD's longitudinal ID crosswalks[12] from the CCD's Reference Library (https://nces.ed.gov/ccd/reference_library.asp) to uniquely identify schools. These stable school IDs became the last 5 digits of the **sedasch** IDs. The final **sedasch** ID is comprised of 12 digits in the same format as the NCES school ID (ncessch). The **sedasch** ID's first 2 digits correspond to the state FIPS code, first 7 digits correspond to a stable geographic district ID (**sedalea**), and the last 5 digits correspond to the school ID within the state. The next section describes how schools were assigned into geographic school districts. This assignment determines the 7-digit stable geographic district ID that is used as the first part of the **sedasch** ID.

Assignment of Schools to Geographic Districts. Most public school districts in the U.S. are geographically defined.[13] In SEDA we use the 2019 EDGE Unified and Elementary School District Boundaries to define geographic school districts. Commonly, public school districts have administrative control over the traditional public schools that fall within their specific geographic boundaries. However, there may be some schools physically located within the geographic boundary of a school district that are not under its administrative control. For example, there may be charter schools or magnet schools located within the boundaries of a school district that are operated by a different school district or a charter school network (which may have no geographic boundary).

In SEDA we have several rules around what schools are placed or excluded from geographic school districts based on location (latitude and longitude coordinates), school type information, and school status information. The aim is for the geographic district test score

[11] See Page 1 in the NCES *School Crosswalk (SY 2014-15 to 2015-16)*. Retrieved from: https://nces.ed.gov/ccd/doc/3_Changes_to_NCES_School_ID_2015_16.docx. Bolding added for emphasis.

[12] *School Crosswalk (SY 2014-15 to 2015-16)*, *School Crosswalk (SY 2015-16 to 2016-17)*

[13] According to NCES, "The US has more than 13,000 geographically defined school districts. These include districts that are administratively and fiscally independent of any other government, as well as public school systems that lack sufficient autonomy to be counted as separate governments and are classified as a dependent agency of some other government—a county, municipal, township, or state. Most public school systems are Unified districts that operate regular, special, and/or vocational programs for children in Prekindergarten through 12th grade." Retrieved from: https://nces.ed.gov/programs/edge/Geographic/DistrictBoundaries

estimates in SEDA to reflect most of the public school students living within the geographic boundaries of the school district. One motivation for this assignment is to better align the average test score estimates with the demographic and socioeconomic data from ACS, which are reported for all families living within geographic school district boundaries.

We use a school's most recently observed CCD information on school operating status, charter status, magnet status, coordinates, and county ID to create time-invariant information for schools in SEDA. Below are the geographic district assignment rules in SEDA based on these time-invariant characteristics:

Charter schools: All (except for special education) charter schools are geolocated and reassigned to the Elementary or Unified District in which they physically reside.

Magnet schools: All (except for special education) magnet schools are geolocated and reassigned to the Elementary or Unified District in which they physically reside.

Schools operated by secondary districts: All schools with NCES LEAIDs corresponding to secondary school districts in the Secondary School District Boundary file are geolocated to the Elementary or Unified geographic district in which they physically reside.

Virtual schools: By their nature, many virtual schools do not draw students from within district geographic boundaries. We identify schools as virtual using CCD data from 2013-14 through 2018-19 Public Elementary/Secondary School Universe Survey Data. The virtual school identifier did not exist in earlier years of data, so we identify virtual schools based on their names. We flag schools as virtual in all years if they were identified as virtual in the last year in which they were observed in the data.[14] We exclude virtual schools from geographic districts, counties, commuting zones, and metropolitan areas.

Special Education Schools: We classify schools as Special Education schools if they are ever classified as "Special Education" in the school-type variable in the CCD data between 2009 and 2019.[15] We exclude these schools from their geographic districts, counties, commuting zones, and metropolitan areas. We do not report test scores for schools with

[14] In 2013-2015, we identified 12 non-virtual schools in Alabama identified as "virtual" by the CCD indicator. We treat these as regular schools in all subsequent steps.

[15] Special Education as defined by School Type in CCD Public Elementary/Secondary School Universe Survey Data

high proportions of students taking alternative tests because their school-average test scores are not comparable to those in other schools. This restriction affects many special education schools.

BIE Controlled Schools: Schools controlled by the Bureau of Indian Education (BIE) are placed in the Elementary or Unified District in which they are physically located.

Schools operated by supervisory unions: Except for special education and virtual schools, we place all schools in Vermont and New York that are part of supervisory unions in their supervisory union LEAs. For example, New York City School District (LEA 3620580) is a supervisory union comprised of 33 subordinate school districts.

District of Columbia Schools: All schools within Washington, DC are given DC's geographic district ID (1100030).

Hawaii Schools: All schools within Hawaii are given Hawaii's geographic district ID (1500030).

All students in a school that is assigned to a particular geographically defined school district will be reflected in that district's estimate. School districts used in SEDA are identifiable by their **sedalea**. You can identify a given school's assigned district by looking at the first 7 digits of the **sedasch** ID, which will be the **sedalea** ID.

School Assignment to Administrative Districts. For each school, we use the NCES leaid provided in CCD in the most recent year the school was observed.

School Assignment to Counties, Metropolitan Statistical Areas, Commuting Zones and States. For each school, we use the county code provided in CCD in the most recent year the school was observed. This county code (**sedacounty**) is stable over time. The county code is then used to merge the school data with the 2013 metropolitan areas and 2010 commuting zones identifiers. Therefore, all schools in SEDA also have a stable metropolitan area (**sedametro**), commuting zone (**sedacz**), and state (**fips**) identifier over time.

Step 2. Data Cleaning

In this step, we first merge the ED*Facts* data (described under **II.A. Source Data**, above) by NCES school ID (**ncessch**) and year with the crosswalk developed in **Step 1**, which matches the ED*Facts* data to the stable unit IDs (**sedasch**, **sedalea**, **sedaadmin**, **sedacounty**, **sedametro**,

sedacz, and **sedafips**) used throughout the SEDA process. We then take two steps to clean the data.

Data Exclusions. We create flags for states (by grade, year, and subject) and schools (by grade, year, and subject) that we intend to drop before estimation.

State removals. Table 4a shows the state-grade-year-subjects for which we produce estimates. Table 4b shows why estimates are not available when they are not. We drop state-year-grade-subjects that meet the following criteria:

Data not reported in ED*Facts*. In some years, data for an individual state-subject-grade may be missing from ED*Facts*. This may be due to many factors. While we do not actively remove these data, they are noted in Table 4b.

State participation is less than 94% or more than 105%: Using the ED*Facts* data, we estimate a participation rate for all state-subject-grade-year cases in the 2012-13 through 2018-19 school years. This participation data file is not available prior to the 2012-13 school year, and therefore we cannot calculate participation rates prior to 2012-13. Participation is the ratio of the number of test scores reported to the number enrolled students in a given state-subject-grade-year:

$$participation_{fygb} = \frac{numscores_{fygb}}{numenrl_{fygb}} \tag{2.1}$$

for each state f, year y, grade g, and subject b. These state-level drops are important because both the quality of the estimates and the linkage process depend on having the full population of student test scores for that state-subject-grade-year. State participation may be low due to a number of factors, including student opt out or pilot testing. Note that we do not drop any entire state-subject-grade-year cases prior to the 2012-13 school year based on participation as enrollment data are not available in ED*Facts*. However, opt out and non-participation was low in 2012-13 (no state was excluded based on this threshold), which suggests states met 94% threshold in prior years when data are not available.

Not all students took the same content tests within the state-subject-grade-year: There are two common ways this appears within the data. First, there are cases where districts were permitted to administer locally selected assessments. This occurred in Nebraska during SY 2008-2009 (RLA and Math) and SY 2009-2010 (Math). Second, in some cases students take end-of-course rather than end-of-grade assessments. When test scores measure different content and are reported on different scales using different cutscores, proficiency counts cannot be compared across districts or schools within these state-subject-grade-year cases.

Different student counts: As an extra check for the completeness of data, we compare the number of test scores in each subject to each other and to the number of enrolled students reported in the CCD. We drop state-year-grade-subjects with (a) less than 90% of the number of test scores reported for the other subject (unless participation in the other subject is higher than 105%), or (b) less than 90% or more than 110% of the number of enrolled students in the CCD.

Insufficient data was reported to ED*Facts*: We remove data from states that reported data from which we cannot recover reliable estimates. In the 2008-09, 2009-10, and 2010-11 school years, Colorado reported data in only two proficiency categories, and a large majority of the data (88% across subjects, grades, and years) fall into a single category. These data do not provide sufficient information to estimate means and/or standard deviations in most regions. In 2016, Tennessee did not complete testing, making their data unreliable.

School removals. We remove two sets of schools at this stage in our process. First, we remove a handful of schools from the data that report data under both BIE school IDs and regular school IDs. These were identified by the NCES. According to the CCD documentation, "There is a possibility that some schools are reported in CCD by both the BIE and the state in which the schools are located, leading to a double counting of students and staff. (NCES allows for the possibility of co-located schools, so a double-counting of schools is not an issue.) This arises from situations where both the state and BIE share operational or financial responsibilities for a school."[16] In order for SEDA to also avoid double counting, we remove the schools from the list and retain their counterparts listed in Table 5**.** Second, we remove schools that appear in EDFacts, but never appear in the CCD from 2009 through 2019. This affects 47 school-years: 11 in 2009, 7 in 2010, 19 in 2013, and no more than 2 in any other year. Most have fewer than 10 assessments across all grades; none have more than 30.

Alternate Assessments. In 2008-09 through 2011-12, ED*Facts* does not distinguish students taking regular from alternate assessments; these counts were combined in the reported data. Therefore, for consistency in all years, we combine the performance data for regular and alternate assessments as reported in ED*Facts*. In some states, alternate assessments have different performance categories relative to the regular assessment.[17] To ensure that the alternate assessment's proficiency levels match the regular assessment's proficiency levels, we collapse the top categories for any places that report students scoring in one higher proficiency level than exists for the regular assessment. The affected state, subject, grade, and year cases include: Arkansas, math and RLA, grades 3-8, years 2012, 2013, and 2014; Colorado, math and RLA, grades 3-8, years 2012, 2013, and 2014; Colorado, RLA, grade 6 in 2018 and 2019; DC, RLA, grade 6 in 2011; Iowa, math and RLA, grades 3 through 8, years 2015 through 2019; and South Carolina, math and RLA, grades 3-8, years 2012-2014.

Step 3. Cutscore Estimation and Linking

In this step, we use HETOP models and the all-student geographic school district proficiency count data to estimate state-subject-grade-year cutscores on a common scale linked to NAEP. We exclude virtual schools from cutscore estimation.

To address practical challenges that can arise in HETOP cutscore estimation for a specific state-subject-grade-year, we:

Rearrange geographic school districts. We reconfigure geographic school districts that meet certain criteria within a state-subject-grade-year in order to improve the HETOP estimation process. First, we combine vectors of counts that have fewer than 20 students

[16] See Page 1 in the NCES *Double Counting of BIE Reported Schools* documentation. Retrieved from: https://nces.ed.gov/ccd/doc/5_Double_Counting_of_Bureau_of_Indian_Education_Schools_3.4.2020.docx
[17] The ED*Facts* documentation notes proficiency levels by assessment type in years after 2011-12.

into "overflow" groups because estimates based on small sample sizes can be inaccurate. Second, in some vectors with more than 20 students the pattern of counts does not provide enough information to estimate a mean or a standard deviation; we also place these count vectors into the "overflow" group. If the resulting overflow groups have parameters that cannot be estimated via maximum likelihood, they are removed from the data. This reconfiguration allows us to retain the maximum possible number of test scores in the estimation sample for the cutscores. This is important as the linking methods we use later in this step rely on having information about the full population in each state-grade-year-subject.

Constrain geographic school districts. For groups not in the "overflow" group, we always estimate a unique mean. But we can sometimes obtain more precise and identifiable estimates by placing additional constraints on group standard deviation parameters in the HETOP model. We constrain standard deviation parameter estimates for groups that meet the following conditions during estimation:

- There are fewer than 50 student assessment outcomes in a geographic school district.
- There are not sufficient data to estimate both a mean and standard deviation (all student assessment outcomes fall in only two adjacent performance level categories; all student assessment outcomes fall in the top and bottom performance categories; or all student assessment outcomes fall in a single performance level category).

After these data processing steps, we estimate a separate HETOP model for each state-subject-grade-year and save the cutscore estimates. For state-grade-year-subjects with only two proficiency categories, we cannot estimate unique geographic school district standard deviations and instead we use the model with a single, fixed standard deviation parameter (the HOMOP model). We denote the estimated cutscores as $\widehat{c}_{1fygb}^{state}, \ldots, \widehat{c_{K-1}}_{fygb}^{state}$, for a state f, year y, grade g, and subject b, where the proficiency data are reported in K categories. These cutscores are expressed in units of their respective state-year-grade-subject student-level standardized distribution. The HETOP model estimation procedure also provides standard errors of these cutscore estimates, denoted $se\left(\hat{c}_{k\,fygb}^{\,state}\right)\ for\ k = 1,..,K-1$, respectively (Reardon, et al., 2017). Note that we do not use the group-specific means or standard deviations that are simultaneously estimated along with the cutscores. See Reardon et al. (2017) for additional details about the HETOP model.

To place these cutscores on a common scale across states, grades, and years we use data from the National Assessment of Educational Progress (NAEP). NAEP data provide estimates of 4th and 8th grade test score means and standard deviations for each state on a common scale, denoted $\hat{\mu}(NAEP)_{fygb}$ and $\hat{\sigma}(NAEP)_{fygb}$, respectively, as well as their standard errors.[18] Because NAEP is administered only in 4th and 8th grades in odd-numbered years, we interpolate and extrapolate linearly to obtain estimates of these parameters for grades (3, 5, 6, and 7) and years (2010, 2012, 2014, 2016, and 2018) in which NAEP was not administered. First, within each NAEP-tested year (2009, 2011, 2013, 2015, 2017, and 2019) 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, and 2018 using the interpolation/extrapolation formulas here:

$$\begin{gathered}
\hat{\mu}(NAEP)_{fygb} = \hat{\mu}(NAEP)_{fy4b} + \frac{g-4}{4}\left(\hat{\mu}(NAEP)_{fy8b} - \hat{\mu}(NAEP)_{fy4b}\right), \\
\text{for g} \in \{3,5,6,7\} \\
\hat{\mu}(NAEP)_{fygb} = \frac{1}{2}\left(\hat{\mu}(NAEP)_{f[y-1]gb} + \hat{\mu}(NAEP)_{f[y+1]gb}\right), \\
\text{for y} \in \{2010, 2012, 2014, 2016, 2018\}
\end{gathered} \tag{3.1}$$

We do the same to interpolate and extrapolate the state NAEP standard deviations. We also do the same for the national NAEP means and standard deviations; these will be used in standardization. The reported national NAEP means and standard deviations, along with interpolated values, by year and grade, are shown in Table 6.

We then use these state-specific NAEP estimates to place each state's cutscores on the NAEP scale. The methods we use—as well as a set of empirical analyses demonstrating the

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

validity of this approach—are described in more detail by Reardon, Kalogrides, and Ho (2019). We provide a brief summary here. Because geographic school district test score moments and the cutscores are expressed on a state scale with mean 0 and unit variance, the estimated mapping of $\widehat{c}_{k_{fygb}}^{state} for\ k = 1, \ldots, K-1$ to the NAEP scale is given by Equation (3.2) below, where $\hat{\rho}_{fygb}^{\text{state}}$ is the estimated reliability of the state test. This mapping yields an estimate of the k^{th} cutscore on the NAEP scale; denoted $\widehat{c}_{k_{fygb}}^{naep}$.

$$\widehat{c}_{k_{fygb}}^{naep} = \hat{\mu}_{fygb}^{naep} + \frac{\widehat{c}_{k_{fygb}}^{state}}{\sqrt{\hat{\rho}_{fygb}^{state}}} \cdot \hat{\sigma}_{fygb}^{naep} \tag{3.2}$$

The intuition behind Equation (3.2) is straightforward: cutscores in states with relatively high NAEP averages should be placed higher on the NAEP scale. The reliability term, $\hat{\rho}_{fygb}^{\text{state}}$, in Equation (3.2) is necessary to account for measurement error in state accountability test scores. Note that cutscores on the state scale are expressed in terms of standard deviation units of the state score distribution. The state scale cutscores are biased toward zero due to measurement error. They must be disattenuated during mapping to the NAEP scale, given that the NAEP scale accounts for measurement error due to item sampling. We disattenuate the means by dividing them by the square root of the state test score reliability estimate, $\hat{\rho}_{fygb}^{\text{state}}$. The reliability data used to disattenuate the estimates come from Reardon and Ho (2015) and were supplemented with publicly available information from state technical reports. For cases where no information was available, test reliabilities were imputed using data from other grades and years in the same state.

Finally, we standardize the NAEP-linked cutscores relative to a reference cohort of students. This standardization is accomplished by subtracting the national grade-subject-specific mean and dividing by the national grade-subject-specific standard deviation for a reference cohort. We use the average of the four national cohorts that were in 4th grade in 2009, 2011, 2013, and 2015. We rescale at this step such that all means recovered in **Step 5** will be 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.

For each grade, year, and subject we calculate:

$$\begin{aligned}\hat{\mu}(NAEP)_{avg,gb} &= \sum_{Y\in\{2005,2007,2009,2011\}} \frac{1}{4}\hat{\mu}(NAEP)_{(y=Y+g)gb} \\ \hat{\sigma}(NAEP)_{avg,gb} &= \sum_{Y\in\{2005,2007,2009,2011\}} \frac{1}{4}\hat{\sigma}(NAEP)_{(y=Y+g)gb}\end{aligned} \tag{3.3}$$

In Equation (3.3), 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 each cutscore:

$$\widehat{c_k}^{cs}_{fygb} = \frac{\widehat{c_k}^{naep}_{fygb} - \hat{\mu}(NAEP)_{avg,gb}}{\hat{\sigma}(NAEP)_{avg,gb}} \tag{3.4}$$

The resulting cutscores are on the CS scale, standardized to this nationally averaged reference cohort within subject, grade, and year.

PARCC & SBAC Cutscores for BIE Waiver Schools. Once we have scaled cutscores, we take all states, years, and subjects that took the PARCC and average their cutscores together to get a set of average PARCC cutscores. We do the same for the SBAC cutscores. These average cutscores are then used for BIE waiver schools taking the respective exams. Table 7a and Table 7b show the states-years-subjects averaged for this cutscore creation.

Applying Cuts to BIE schools. Some BIE schools submitted data in different proficiency categories than the proficiency categories reported by the states in which the BIEs reside. In addition, the Navajo Nation had test waivers for the PARCC beginning in SY 2015-16 and Miccosukee Indian School which had a waiver for the SBAC starting in SY 2014-15. For these waiver schools, we use the averaged waiver cuts discussed above. For non-waiver BIE schools, we realign the BIE cuts to match the cuts for the states in which they were located. A few schools whose cuts we could not determine were omitted from SEDA. See Table 8.

Step 4. Selecting Data for Mean Estimation

In Step 5, we estimate a model separately for each unit-subgroup that draws only on the subject-grade-year data for that unit-subgroup. For some subjects, grades, and years, we are less confident in the quality of the unit-subgroup data and do not want to include these in the estimation as it may bias the parameter estimates.[19] We create flags for dropping these cases, which are described below:

There is only 1 test score for the unit-year-subject-grade. There is insufficient data to construct test score means and standard deviations for these cells.

The participation rate is less than 95%. In these cases, the population of tested students may not be representative of the population of students in that school. Therefore, we flag and remove all unit-subgroup-subject-grade-year cases where participation was lower than 95%. Participation is defined as:

$$participation_{urygb} = \frac{numscores_{urygb}}{numenrl_{urygb}}. \tag{4.1}$$

This measure can be constructed starting in the 2012-13 school year; we do not remove data based on this rule in earlier years. If the participation rate for "all students" is less than 95%, we do not report any estimates for demographic subgroups regardless of whether the subgroup-specific participation rate was greater than 95% because we are concerned about data quality in cases with low overall participation.

Incomplete data reported by student demographic subgroups. There are a small number of cases where the total number of test scores reported by race or gender is less than 95% of the total reported test scores for all students. For example, there may be 50 test scores reported for all students, but only 20 test scores for male students and 20 test scores for female students. In this case, we would not report the male or female test score means because insufficient test scores were reported by gender. We calculate the reported percentage as:

$$representation_{urygb} = \frac{\sum_r numscores_{urygb}}{numscores_{u,all,ygb}}. \tag{4.2}$$

[19] This logic of this data selection differs from the cleaning done in Step 2 to support cutscore estimation. For the cutscore estimation, we wanted to keep as much data as possible in the estimation process because the linking procedure at the end of Step 3 requires population-based data. Moreover, the cutscores are not particularly sensitive to low-quality data for individual geographic school districts. In contrast, the individual school/geographic district mean/SD estimates will be strongly affected by low quality data (which is defined and described in this section).

This measure can be constructed in all years. We flag and remove unit-subgroup-subject-grade-year data from SEDA where there is not at least a 95% representation rate for the gender or race subcategories.

More than 40% of students take alternate assessments. Measurement error may affect unit-subgroup-subject-grade-year cases where over 40% of the students take alternate assessments. These assessments typically differ from the regular assessment and have different proficiency thresholds. This flag can be constructed starting in the 2012-13 school year; we do not apply this rule in earlier years. We flag and remove places that meet this criterion from SEDA at this step.

Insufficient data. In some cases, the data we have does not meet the minimum statistical estimation requirements. First, we flag and remove all unit-subgroup-subject-grade-years where 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. Second, we flag unit-subgroup-subject-grade-year cells as insufficient if:

1. All observations are in a single, middle proficiency category.
2. All observations are in only 2 adjacent proficiency categories.
3. All observations are only in the top and bottom proficiency categories.

We remove all unit-subgroup-subjects where *all* grade-year cells are insufficient. We will be unable to produce estimates in these cases as there is insufficient data to freely estimate a mean and standard deviation in any cell.

Table 9 shows how many unit-subgroup-subject-grade-years cells these drops affect and what is excluded from mean estimation.

Flags for estimation. We create two flags for use in estimation: an "insufficient data" flag and a "size" flag. During estimation, the insufficient data and size flags are used to place constraints on the standard deviation estimates for individual grade-year cells.

Insufficient data flag. Unit-subgroup-subjects may contain one or more "insufficient" grade-year cells which do not have sufficient data to freely estimate both a mean and a standard deviation. A grade-year cell will be insufficient if:

1. All observations are in a single, middle proficiency category.

2. All observations are in only 2 adjacent proficiency categories.
3. All observations are only in the top and bottom proficiency categories.

Size flag. We flag cells as "small" if they have fewer than 100 test scores; otherwise, cells are flagged as "large".

Step 5. Estimating Test Score Means

The goal of this step is to estimate the mean and standard deviation of test scores for each subgroup in each unit (schools, geographic districts, administrative districts, counties, metropolitan areas, commuting zones, or states) across subjects, grades, and years.

Pooled HETOP estimation. In the prior steps, we prepared two pieces of information that we use in estimation: the observed proficiency counts for each unit-subgroup-grade-year-subject from **Step 4** and the estimated cutscores separating the proficiency categories in the associated state-grade-year-subject from **Step 3**. All schools are affiliated with a single state and, thus, a single test and a single set of cutscores. While larger units (geographic districts, administrative districts, metropolitan areas, commuting zones, and states) are also typically affiliated with a single state, test, and set of cutscores, there are a few notable exceptions:

Units that contain BIE schools: As noted above, BIE schools often have different cutscores than the other schools assigned to a unit. In these cases, the unit is split into two or more components where the schools assigned to each component take the same test and use the same cutscores. For example, we might split a unit into two pieces: unit-regular schools and unit-BIE waiver schools.

Metropolitan Areas or Commuting Zones that cross state lines: A subset of metropolitan areas and commuting zones cross state lines and therefore can be affiliated with several state's cutscores. We split these units into metropolitan area-by-state or commuting zone-by-state components, where the schools assigned to each component took the same test and used the same cutscores.

For both cases, we estimate pooled HETOP using data for each subcomponent and the appropriate cutscores, we then aggregate the components after estimation into overall unit estimates.

A pooled HETOP model (Shear & Reardon, 2021; Reardon et al., 2017) to estimate μ^{cs}_{urygb} and σ^{cs}_{urygb}, the mean and standard deviation of achievement on the CS scale for unit u, subgroup r, year y, grade g, and subject b. As described below, the pooled HETOP model is estimated separately for each unit-subgroup-subject but combines data across grades and years when estimating these parameters. Combining data across grades and years allows us to get better estimates of σ^{cs}_{urygb} for years and grades in which sample sizes are small or where the proficiency count data are limited.

We use a pooled HETOP model to overcome three practical challenges. The challenges are: 1) in some states, years, and grades, the number of proficiency categories $K = 2$ and there is not sufficient information to estimate both a mean and a standard deviation for each unit-subgroup-grade-year-subject; 2) if $K \geq 3$ but there are sampling zeros because test scores were not observed in all K categories for a particular grade and year, there may not be sufficient information to estimate both a mean and a standard deviation; and 3) when the sample size n_{kurygb} is small, prior simulations (e.g., Reardon et al., 2017; Shear & Reardon, 2021) have shown that estimates of standard deviations can be biased and contain excessive sampling error.

We estimate a pooled HETOP model (Shear & Reardon, 2021) for each unit, separately for each subject and subgroup, by “pooling” data across all available grades and years, and maximizing the joint log likelihood function given by:

$$L = \ln\left[P\left(\mathbf{N}_{urb} \middle| \mathbf{M}^{cs}_{urb}, \mathbf{H}^{cs}_{urb}, \mathbf{C}^{cs}_{fb}\right)\right] = \sum_{y=1}^{Y}\sum_{g=1}^{G}\sum_{k=1}^{K} n_{kurygb} \ln\left(\pi_{kurygb}\right)$$

$$= \sum_{y=1}^{Y}\sum_{g=1}^{G}\sum_{k=1}^{K_{gy}} n_{kurygb} \ln\left(\Phi\left(\frac{\mu^{cs}_{urygb} - c^{cs}_{k-1_{fygb}}}{\exp\left(h_{urb}(g,y)\right)}\right) - \Phi\left(\frac{\mu^{cs}_{urygb} - c^{cs}_{k_{fygb}}}{\exp\left(h_{urb}(g,y)\right)}\right)\right),$$

where $\mathbf{N}_{urb}$ is a matrix of proficiency counts across all available grades (G) and years (Y) for unit u, subgroup r and subject b, $\mathbf{M}^{cs}_{urb}$ is a vector of estimated means across grades and years, $\mathbf{H}^{cs}_{urb}$ is a vector of estimated parameters for the function $h(\quad)$ described below, and $\mathbf{C}^{cs}_{fb}$ is a matrix of cutscores across grades and years. The cutscores are treated as fixed here, using the values estimated in **Step 3**. We have replaced σ_{urygb}^{cs} in the above equation with $\exp\left(h_{urb}(g,y)\right)$, where $h_{urb}(g,y)$ is a unit-specific function used to model the natural log of the standard deviations as a function of grade and year:

$$h_{urb}(g,y) = \ln\left(\sigma_{urygb}^{cs}\right) = \gamma_{urygb}^{cs}.$$

We do this for two reasons. First, estimating $\gamma_{urygb}^{cs} = \ln\left(\sigma_{urygb}^{cs}\right)$ rather than σ_{urygb}^{cs} directly ensures that the ML estimate will be positive. Second, defining γ_{urygb}^{cs} as a function of grade and year, rather than allowing this value to be unique in each grade and year, defines the pooled HETOP model. If we place no constraints on the model and allow $h_{urb}(g,y) = \gamma_{urbgy}$ to take on a unique value in each grade and year, maximization of this likelihood will result in identical estimates to those obtained by maximizing the likelihood separately for each grade and year.

To leverage the data available across multiple grades and years and overcome the limitations noted above, we define $h_{urb}(g,y)$ in the following way. First, we allow γ_{urygb} to be freely estimated in each grade-year cell that is both "sufficient" and "large", by the flags defined above. For all other grade-year cells, we constrain $h_{urb}(g,y)$ such that the estimate of γ_{urygb} is equal to the mean of the $\hat{\gamma}_{urygb}$ estimates across the freely estimated cells. That is, we estimate a common "pooled" standard deviation across the grades and years in which there are "insufficient data" and/or "small" cell sizes.

More formally, for all years and grades in which $n_{urygb} < 100$ and/or in which there are insufficient data to estimate both a mean and a standard deviation, we constrain $h_{urb}(g,y) = \gamma_{urb}^{cs}$ to be equal, while allowing $h_{urb}(g,y) = \gamma_{urygb}^{cs}$ to be freely estimated in grades and years with at least 100 test scores and sufficient data to estimate both a mean and standard deviation. We further constrain the model such that the "pooled" log standard deviation is equal to the (unweighted) mean of the unconstrained log standard deviations by defining the constraint:

$$\gamma_{urb}^{cs} = \frac{\sum_{g=1}^{G}\sum_{y=1}^{Y}\left(I_{urygb}^{100} \cdot I_{urygb}^{S} \cdot \gamma_{urygb}^{cs}\right)}{\sum_{g=1}^{G}\sum_{y=1}^{Y}\left(I_{urygb}^{100} \cdot I_{urygb}^{S}\right)},$$

where I_{urygb}^{100} is the size indicator flag (equal to 1 if size is "large") and $I_{urygb}^{S}$is the sufficient data indicator flag (equal to 1 if there are sufficient data). If I_{urygb}^{100} and I_{urygb}^{S} are equal to 1 for all cells in a unit, then we estimate a unique mean and standard deviation for each cell. For all other units, there will be a mix of freely estimated and constrained standard deviation parameters.

Recall in **Step 4** that we removed unit-subgroups where $I^{S}_{urygb} = 0$ for all cells because we are unable to estimate a standard deviation parameter.

In sum, the models described here are used to produce ML estimates of μ^{cs}_{urygb} and σ^{cs}_{urygb} (where $\hat{\sigma}^{cs}_{urygb}$ may be constrained to be equal in some grades and years), as well as estimated standard errors $se\left(\hat{\mu}^{cs}_{urygb}\right)$ and $se\left(\hat{\sigma}^{cs}_{urygb}\right)$ and the estimated sampling covariances $cov\left(\hat{\mu}^{cs}_{urygb}, \hat{\sigma}^{cs}_{urygb}\right)$. The estimates are produced on the CS scale described elsewhere, and can be transformed to other scales, as described in **Step 6**.

Aggregating unit components. For the subset of units where we split the unit into components for pooled HETOP estimation, we need to "re-aggregate" the components into complete unit estimates. The following summary is written for metropolitan areas that cross state lines; however, the same logic can be applied to units serving BIE schools or commuting zones that cross state lines. Suppose there are a set of M metropolitan areas that cross state lines (e.g., have two or more metropolitan area-by-state components). The metropolitan area mean is then estimated as the weighted average of metropolitan area-by-state means across all D_m metropolitan area components in metropolitan area m, computed as

$$\hat{\mu}^{cs}_{mrygb} = \sum_{d=1}^{D_m} p_{dm} \hat{\mu}^{cs}_{mrygb}, \tag{5.1}$$

where p_{dm} is the proportion of metropolitan area m represented by metropolitan area-by-state component d. The estimated metropolitan area standard deviation is estimated as the square root of the estimated total variance between and within metropolitan area-by-state components in the metropolitan area,

$$\hat{\sigma}^{cs}_{mrygb} = \sqrt{\hat{\sigma}^2_{B_m} + \hat{\sigma}^2_{W_m}} \tag{5.2}$$

where $\hat{\sigma}^2_{B_m}$ is the estimated variance between metropolitan area-by-state components in metropolitan area m and $\hat{\sigma}^2_{W_m}$ is the estimated variance within metropolitan area-by-state components in metropolitan area m. The formulas used to estimate $\hat{\sigma}^2_{B_m}$ and $\hat{\sigma}^2_{W_m}$ are based on equations in Reardon et al. (2017). These formulas and formulas for estimating the standard errors of the metropolitan area means and standard deviations, $\hat{\mu}_{mrygb}^{cs}$ and $\hat{\sigma}_{mrygb}^{cs}$, are included in Appendix A1.

Step 6. Creating Additional Reporting Scales

As described in **Step 3**, we standardize the cutscores prior to estimation such that all mean estimates are produced on the CS scale. In this step, we establish a second scale: The **Grade Cohort Standardized (GCS) scale.** We recommend CS-scaled estimates for research purposes and the GCS-scaled estimates for low-stakes reporting to non-research audiences.

Recall that the CS scale is standardized within subject and grade, relative to the average of the four cohorts in our data who were in 4th grade in 2009, 2011, 2013, and 2015. We use the average of four cohorts as our reference group because they provide a stable baseline for comparison. This metric is interpretable as an effect size, relative to the grade-specific standard deviation of student-level scores in this common, average cohort. For example, a district mean of 0.5 on the CS scale indicates that the average student scored approximately one half of a standard deviation higher than the average national reference cohort scored in that same grade. Means reported on the CS scale have an overall average near 0 as expected. Note that this scale retains information about absolute changes over time by relying on the stability of the NAEP scale over time. This scale does not enable absolute comparisons across grades, however.

Unit means on the GCS scale are standardized relative to the average difference in NAEP scores between students one grade level apart. The average grade-level difference in national NAEP scores is estimated as the within-cohort grade-level change (separately by subject b), for the average of four cohorts of students in 4th grade in 2009, 2011, 2013, and 2015 (see detail on how $\hat{\mu}(NAEP)_{avg,gb}$ and $\hat{\sigma}(NAEP)_{avg,gb}$ are calculated in **Step 3**). It is denoted $\hat{\gamma}_{avg,b}$:

$$\hat{\gamma}_{avg,b} = \frac{\hat{\mu}(NAEP)_{avg,8b} - \hat{\mu}(NAEP)_{avg,4b}}{4} \tag{6.1}$$

We then identify the linear transformation that sets the grade 4 and 8 averages for this cohort at the “grade level” values of 4 and 8 respectively. Then transform unit means, standard deviations, and their variances accordingly:

$$\hat{\mu}_{urygb}^{gcs} = 4 + \frac{\hat{\mu}(NAEP)_{avg,gb} - \hat{\mu}(NAEP)_{avg,4b}}{\hat{\gamma}_{avg,b}} + \frac{\hat{\sigma}(NAEP)_{avg,gb}}{\hat{\gamma}_{avg,b}} \hat{\mu}_{urygb}^{cs} \tag{6.2}$$

$$var\left(\hat{\mu}^{gcs}_{urygb}\right) = \left(\frac{\hat{\sigma}(NAEP)_{avg,gb}}{\hat{\gamma}_{avg,b}}\right)^2 var\left(\hat{\mu}^{cs}_{urygb}\right) \tag{6.3}$$

$$\hat{\sigma}^{gcs}_{urygb} = \frac{\hat{\sigma}(NAEP)_{avg,gb}}{\hat{\gamma}_{avg,b}} \hat{\sigma}^{cs}_{urygb} \tag{6.4}$$

$$var\left(\hat{\sigma}^{gcs}_{urygb}\right) = \left(\frac{\hat{\sigma}(NAEP)_{avg,gb}}{\hat{\gamma}_{avg,b}}\right)^2 var\left(\hat{\sigma}^{cs}_{urygb}\right) \tag{6.5}$$

Then, $\hat{\mu}^{gcs}_{urygb}$ can be interpreted as the estimated average national "grade-level performance" of students in unit u, subgroup r, year y, grade g, and subject b. For example, if $\hat{\mu}^{gcs}_{ury4b} = 5$, 4th-grade students in unit u, subgroup r, and year y are one grade level ($\hat{\gamma}_b$) above the 4th grade 2009-2015 national average ($\hat{\mu}(NAEP)_{avg,4b}$) in performance on the tested subject b.

This metric enables absolute comparisons across grades and over time, but it does so by relying not only on the assumption that the NAEP scale is stable over time but also that it is vertically linked across grades 4 and 8 and linear between grades. This metric is a simple linear transformation of the NAEP scale, intended to render the NAEP scale more interpretable. For reference, 1 CS scale standard deviation is approximately 3 grade levels. As such, this metric is useful for presenting descriptive research to broad audiences not familiar with interpreting standard deviation units. However, we do not advise it for analyses where the vertical linking across grades and the linear interpolation assumptions are not required nor defensible.

Step 7. Calculating Achievement Gaps

We calculate achievement gap estimates in SEDA 5.0 for all units except schools. Gaps are estimated as the difference in average achievement between subgroups, using the mean estimates from Steps 5 and 6. We calculate White-Black (wbg), White-Hispanic (whg), White-Asian (wag), White-Native American (wng), male-female (mfg), and nonECD-ECD (neg) achievement.

In each scale, the unit-subject-grade-year gap is given by the difference in the means, e.g., the White-Black gap is given by:

$$\widehat{wbg}^{x}_{uygb} = \hat{\mu}^{x}_{u(r=wht)ygb} - \hat{\mu}^{x}_{u(r=blk)ygb} \tag{7.1}$$

where x denotes a particular scale (CS, GCS) described in **Steps 3** and **7** above. The standard error of the gap is given by:

$$se\left(\widehat{wbg}^{x}_{uygb}\right) = \sqrt{se\left(\hat{\mu}^{x}_{u(r=wht)ygb}\right)^2 + se\left(\hat{\mu}^{x}_{u(r=blk)ygb}\right)^2} \tag{7.2}$$

The gaps, reported in the CS and GCS scales, can be interpreted similarly to the means. If one or both of the subgroup means needed for the calculation is not available or excluded in a given unit-subject-grade-year, the gap estimate will be missing.

Step 8. Pooled Estimates

For each unit-subgroup, we have up to 132 subject-grade-year mean estimates (11 years, 6 grades, 2 subjects). We pool the estimates using precision-weighted random-coefficient models to produce:

1. Subject-specific pooled estimates. Pooled over grades and cohorts within subject (“poolsub”)
2. Overall pooled estimates. Pooled over grades, cohorts, and subjects (“pool”)

For geographic school districts, administrative school districts, counties, metropolitan areas, commuting zones, and states, we provide both subject-specific and overall pooled estimates. For schools we provide only estimates pooled over grades, cohorts, and subjects (“overall pooled estimates” or “pool” estimates).

For each of the following model-types, we estimate a single model drawing on data for all 50 states plus DC to recover pooled estimates. We use all available long form data for all units. For simplicity the subscript for subgroup is dropped from the equations below; models are estimated separately by subgroup. In SEDA 5.0, we produce subject-specific and overall pooled estimates for all subgroups and gaps. See the subsection **Pooled Gap Estimates** for interpretation differences.

<u>Subject-Specific Pooled Estimates.</u> This model allows each unit-subgroup to have a subject-specific intercept (average test score), a subject-specific linear grade slope (the “learning rate”), and a subject-specific cohort trend (the “trend”). We fit the following model for all units except schools:

$$
\begin{aligned}
\hat{\mu}^{x}_{uygb} = {} & \left[\beta_{0mu} + \beta_{1mu}\left(cohort_{uygb} - mc\right)\right. \\
& \left. + \beta_{2mu}\left(grade_{uygb} - mg\right)\right] M_b \\
& + \left[\beta_{0eu} + \beta_{1eu}\left(cohort_{uygb} - mc\right)\right. \\
& \left. + \beta_{2eu}\left(grade_{uygb} - mg\right)\right] E_b + \epsilon_{uygb} + e_{uygb} \\
\beta_{0mu} = {} & \gamma_{0m0} + v_{0mu} \\
\beta_{1mu} = {} & \gamma_{1m0} + v_{1mu} \\
\beta_{2mu} = {} & \gamma_{2m0} + v_{2mu} \\
\beta_{0eu} = {} & \gamma_{0e0} + v_{0eu} \\
\beta_{1eu} = {} & \gamma_{1e0} + v_{1eu} \\
\beta_{2eu} = {} & \gamma_{2e0} + v_{2eu} \\
e_{uygb} \sim {} & N\left(0, \widehat{\omega}^2_{uygb}\right);\ \epsilon_{uygb} \sim N(0, \sigma^2); \begin{bmatrix} v_{0mu} \\ \vdots \\ v_{2eu} \end{bmatrix} \sim MVN(0, \boldsymbol{\tau}^2).
\end{aligned}
\tag{8.1}
$$

M_b is an indicator variable equal to 1 if the subject is math and E_b is an indicator variable equal to 1 if the subject is RLA. $grade$ is the grade-level. We center grade at the middle grade of our sample, $mg = \frac{3+8}{2} = 5.5$. $cohort$ is defined as $year - grade$. We center cohort at the middle cohort of our data, $mc = \left(\frac{2019-2009}{2} - \frac{8-3}{2}\right) = (2014 - 5.5) = 2008.5$. e_{uygb} is a normally distributed error term with mean zero and known variance equal to the sampling variance of the mean. The residual variance σ^2 and components of $\boldsymbol{\tau}^2$ are estimated.

In this model, β_{0bu} represents the mean test score in subject b, in unit u, in grade 5.5 for the 2008.5 cohort. The β_{1bu} parameter indicates the average within-grade (cohort-to-cohort) change per year in average test scores in unit u in subject b; and the β_{2bu} indicates the average within-cohort change per grade in average test scores in unit u in subject b. If the model is fit using the CS scaled estimates (cs), the coefficients will be interpretable in NAEP student-level standard deviation units (relative to the specific standard deviation used to standardize the scale). Between-unit differences in β_{0bu}, β_{1bu}, and β_{2bu} will be interpretable relative to this same scale. If the model is fit using the GCS scaled estimates (gcs), the coefficients will be interpretable as test score differences relative to the average between-grade difference among students.

Overall Pooled Estimates. This model pools data across grades, years, and subjects to produce overall unit estimates. This model allows each unit to have a unit-specific intercept (average test score, pooled over subjects), linear grade slope (the average "learning rate" at which scores change across grades, within a cohort, pooled over subjects), cohort trend (the average "trend," or rate at which scores change across student cohorts, within a grade, pooled over subjects), and the math-RLA difference.

For all units, we fit this model is as follows:

$$\begin{aligned}
\hat{y}^{x}_{uygb} &= \beta_{0u} + \beta_{1u}\left(cohort_{uygb} - mc\right) + \beta_{2u}\left(grade_{uygb} - mg\right) \\
&\qquad + \beta_{3u}(M_b - .5) + \epsilon_{uygb} + e_{uygb} \\
\beta_{0u} &= \gamma_{00} + v_{0u} \\
\beta_{1u} &= \gamma_{10} + v_{1u} \\
\beta_{2u} &= \gamma_{20} + v_{2u} \\
\beta_{3u} &= \gamma_{30} + v_{3u} \\
e_{uygb} &\sim N\left(0, \hat{\omega}^2_{uygb}\right);\ \epsilon_{uygb} \sim N(0, \sigma^2); \begin{bmatrix} v_{0u} \\ v_{1u} \\ v_{2u} \\ v_{3u} \end{bmatrix} \sim MVN(0, \boldsymbol{\tau}^2).
\end{aligned} \tag{8.2}$$

$grade$ is the grade-level, which is centered at mg. For all units except schools, $mg = \frac{3+8}{2} = 5.5$, the middle grade of our sample. For schools, $mg_n = \frac{\max(grade)_n + \min(grade)_n}{2}$, the middle grade of the school for which we have test score estimates from **Step 5**, regardless of whether the school serves additional grades or tested in other grades for which we could not produce estimates. For reference, the grade spans of schools are shown in Table 10. $cohort$ is the cohort defined as $year - grade$; it is centered at mc. For all units except schools, $mc = \left(\frac{2019+2009}{2} - \frac{3+8}{2}\right) = (2014 - 5.5) = 2008.5$, the middle cohort of our sample. For schools, we define $mc_n = \left(\frac{2019+2009}{2} - mg_n\right)$. Note that we use this same middle year, $\frac{2019+2009}{2}$, for cohort centering regardless of whether the school was observed over that whole time period. M_b is an indicator variable equal to 1 if the subject is math. For all units, we center M_b at 0.5 so that the intercept represents the average of math and RLA. e_{uygb} is a normally distributed error term with mean zero and known variance equal to the sampling variance of the mean. The residual variance σ^2 and components of $\boldsymbol{\tau}^2$ are estimated.

In this model, β_{0bu} represents the mean test score in unit u in grade 5.5 for the 2008.5 cohort, averaging across math and RLA. The β_{1bu} parameter indicates the average within-grade (cohort-to-cohort) change per year in average test scores in unit u; and the β_{2bu} indicates the average within-cohort change per grade in average test scores in unit u. If the model is fit using the CS standardized estimates ($x = cs$), the coefficients will be interpretable in NAEP student-level standard deviation units (relative to the specific standard deviation used to standardize the scale). Between-unit differences in β_{0bu}, β_{1bu}, and β_{2bu} will be interpretable relative to this same scale. If the model is fit using the GCS standardized estimates ($x = gcs$), the coefficients will be interpretable as test score differences relative to the average between-grade difference among students.

Tables 11a-g report the variance and covariance terms from the $\hat{\boldsymbol{\tau}}^2$ matrices and Tables 12a-g report the estimated reliabilities from estimated by the pooling models for all units.

Pooled Gap Estimates. We use the models in Equations (8.1) and (8.2) to pool gaps in geographic districts, administrative districts, counties, metropolitan areas, commuting zones, and states. For example, the pooled White-Black gap parameter estimates in unit u are obtained by 1) computing the gap (the difference in mean White and Black scores) in each unit-grade-year-subject; and 2) fitting the models in Equations (8.1) and (8.2) above using these gaps on the left-hand side. However, notably the interpretation of the estimated pooling model coefficients differs. These models recover the average test score gap across grades and years, the rate of the gap changes over grades within cohorts, and the trend in the gap across cohorts within grades.

For users interested in analyzing pooled achievement gaps, it is important to use the pooled gap estimates (described above) rather than taking the difference between pooled estimates of group-specific means.[20] For example, taking the difference of pooled White and

[20] Taking the difference of the pooled means would entail: 1) fitting model (8.1) or (8.2) above using the White mean estimates on the left-hand side; 2) constructing $\hat{\beta}^{ols}_{0u(r=wht)}$ and $\hat{\beta}^{eb}_{0u(r=wht)}$ for White students from the estimates; 3) doing the same with Black student mean scores to construct $\hat{\beta}^{ols}_{0u(r=blk)}$ and $\hat{\beta}^{eb}_{0u(r=blk)}$ for Black students; and then 4) estimating gaps by subtracting $\hat{\beta}^{ols}_{0u(r=wht)} - \hat{\beta}^{ols}_{0u(r=blk)}$ and $\hat{\beta}^{eb}_{0u(r=wht)} - \hat{\beta}^{eb}_{0u(r=blk)}$.

Black mean scores will not yield the same White-Black pooled gap estimates as the above approach because the difference in the EB shrunken means is not generally equal to the EB shrunken mean of the gaps. The latter (using the pooled gaps) is preferred.

OLS and EB Estimates from HLM Models. SEDA 5.0 contains two sets of estimates derived from the pooling models described in Equations (8.1) and (8.2): (1) the OLS estimates and (2) the Empirical Bayes (EB) shrunken estimates. The OLS estimates are the estimates that we would get if we took the fitted values from Equations (8.1) and (8.2) and added in the residuals. For example, from Equation (8.2): $\hat{\beta}_{0u}^{ols} = \hat{\gamma}_{00} + \hat{v}_{0u}$. These are unbiased estimates, but they may be noisy in small units. We obtain standard errors of these as described in Appendix A2.

The EB estimates are based on the fitted model as well, but they include the EB shrunken residual. For example, from Equation (8.2): $\hat{\beta}_{0u}^{eb} = \hat{\gamma}_{00} + \hat{v}_{0u}^{eb}$, where $\hat{v}_{0u}^{eb}$ is the EB residual from the fitted model. The EB estimates are biased toward the grand mean but have statistical properties that make them suited for inclusion as predictor variables or when one is interested in identifying outlier units. We report the square root of the posterior variance of the EB estimates as the standard error of the EB estimate.

In general, the EB estimates (marked as “eb” in the data files) should be used for descriptive purposes and as predictor variables on the right-hand side of a regression model; they are the estimates shown on the website (https://edopportunity.org). They should not be used as outcome variables in a regression model because they are shrunken estimates. Doing so may lead to biased parameter estimates in fitted regression models. The OLS estimates (marked as “ol” in the data files) are appropriate for use as outcome variables in a regression model. When using the OLS estimates as outcome variables, we recommend fitting precision-weighted models that account for the known error variance of the OLS estimates.

Replicating Pooled Estimates. The input data that we use to construct the pooled estimates are the non-noised long-form estimates prior to data suppression, described in **Step 9**. Users will not be able to identically replicate our pooled estimates given two differences between the public long files and the ones used to create the pooled estimates: added noise and fewer estimates (described in more detail below). However, the results should be similar.

Step 9. Suppressing Data for Release

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;[21] and (2) that a small amount of random noise is added to each estimate in proportion to the sampling variance of the respective estimate. 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 to unit-subgroup estimate is drawn from a normal distribution $\mathcal{N}(0,(1/n)*\widehat{\omega}^2)$ where $\widehat{\omega}^2$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. For gaps, we use the same formula, but n is equal to the number of student assessment outcomes for the smaller of the two groups.

In addition, 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 ED*Facts* 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. Table 13 summarizes the cases removed in the long files.

Pooled Files. For all pooled files, our agreement with the US Department of Education requires that all reported mean estimates (1) reflect at least 20 unique students; and (2) are pooled across at least two subject-year-grades. For gap estimates, we require that each group has at least 20 unique students and is pooled across at least two subject-year-grades.

For a small number of units, there is insufficient data to recover an OLS estimate or SE for a given parameter. While we are able to recover EB estimates for these parameters, we do not release them. Moreover, in the interest of discouraging the over-interpretation of imprecisely

[21] In the case of gap estimates, we require that each group has at least 20 unique students in each reported cell.

estimated parameters, SEDA 5.0 does not report EB or OLS parameter estimates (the average test score, learning rate, or trend in average test score) for a unit when the OLS reliabilities of the individual parameter are below 0.7. We compute the reliability of each OLS parameter estimate $\hat{\beta}_{ku}^{ols}$ as $\frac{\hat{\tau}_k^2}{\hat{\tau}_k^2+\hat{V}_{ku}}$, where $\hat{\tau}_k^2$ is the k^{th} diagonal element of the $\hat{\boldsymbol{\tau}}^{\mathbf{2}}$ matrix (the estimated true variance of β_{kd}) and $\hat{V}_{ku}$ is the square of the estimated standard error of $\hat{\beta}_{ku}^{ols}$. That is, we do not report $\hat{\beta}_{ku}^{ols}$ if $\hat{V}_{ku} > \frac{3}{7}\hat{\tau}_k^2$. For subgroups, we use the same procedure and for gaps we additionally suppress the estimate if either or both subgroups are suppressed (e.g., suppress White-Black gap if either White and/or Black estimates are suppressed). We use the standard error threshold determined for all students to censor estimates rather than calculate a subgroup-specific threshold. In the case where the reliability of the intercept (average test score) for a unit is less than 0.7, we do not report any parameter estimates for that unit. We also remove all estimates associated with units that are based on more than 20% alternate assessments across the grades and years in the ED*Facts* data. We suppress all subgroup estimates if the mean is missing for the "all" subgroup. Finally, we suppress estimates whenever the mean or standard error of the mean is missing. Table 14 summarizes the cases removed in the pooled files.

II.F. Additional Notes

Gender Mean and Gap Estimates. Recent research reported by Reardon, Kalogrides, et al. (2019) suggests that the magnitude of gender achievement gaps can be impacted by the proportion of test items that are multiple-choice versus constructed-response. As a result, differences in gender gaps across states (or across time when a state changes the format of its test) may confound true differences in achievement with differences in the format of the state test used to measure achievement. See Reardon, Fahle, et al. (2019) for a description of an analytic strategy that can be used to adjust for these potential effects.

Charter School Estimates. Research reported in Reardon, Papay, et al. (2019) shows that estimates of student learning rates (the coefficient on the "grade" term in the pooling models in Step 8) are generally unbiased and reliable, except when student mobility in and out of schools is high. In the three states' data they used, student mobility was higher, on average, in small schools and districts, schools with long grade spans, and in charter schools. In addition, in very small schools and charter schools, the estimated grade slope is biased upwards, as a result of differential mobility (more lower-achieving students leave schools than enter). As a result, we recommend that users interpret the school level grade slopes with some caution, particularly for small schools, schools that span 4 or more of the grades from 3 to 8, and charter schools. Moreover, users should be cautious in comparing grade slopes in charter schools to those of traditional public schools, given the evidence of systematic upward bias in the charter sector estimates.

II.G. How to Obtain Values Shown on edopportunity.org

In order to replicate the values shown on the EdOpportunity website from the downloadable data files (csv/Stata), please refer to the steps below:

1. Determine what geography you would like to focus on and download the corresponding GCS Pooled File: **seda_[geography]_pool_gcs_[seda_version]**, where **geography** is *school*, *geodist*, or *county* and where **seda_version** is a number, e.g., *5.0* for version 5.0.
2. To get average test score, do the following calculation: gcs_mn_avg_eb – gradecenter
3. To get the learning rate, do the following calculation: gcs_mn_grd_eb – 1
4. To get the trend, use gcs_mn_coh_eb
5. In order to get the corresponding Margins of Error (we use a 95% confidence interval) on our site, multiply the Standard Errors on the variable you would like to use by 1.959964 (the inverse cumulative standard normal distribution of .975). For example, to get the average test score margin of error, that would be gcs_mn_avg_eb_se * 1.959964. If you are working in Stata, you could also use gcs_mn_avg_eb_se * invnormal(.975).

III. Covariate Data Construction

SEDA 5.0 contains CCD and ACS data that have been curated for use with the school, geographic school district, administrative school district, county, metropolitan area, and state achievement data.

III.A. ACS Data and SES Composite Construction

For geographic and administrative districts, counties, metropolitan areas and states we use data from the ACS to construct measures of median family income, proportion of adults with a bachelor's degree or higher, proportion of adults that are unemployed, the household poverty rate, the proportion of households receiving SNAP benefits, and the proportion of households with children that are headed by a single mother. We also combine these measures to construct a single socioeconomic status composite.

ACS data are available as 5-year pooled samples, from which we use samples from 2005-2009 through 2015-2019. The samples we use here reflect data for the total population of residents in each unit. In select years, district-level tabulations are also available for families who live in each school district in the U.S and who have children enrolled in public school. However, the most recent sample of this data that has all of the information we need is the 5-year 2007-2011 sample. We prefer to use the total population tabulation data from more recent years. We have compared measures constructed using the total population samples and the relevant children enrolled in public schools samples in years where both samples are available and the measures are highly correlated ($r > 0.99$) and not sensitive to which sample we use.

The construction of our derived measures from the ACS data occurs in a variety of steps, which we describe below. Our derivation of these measures is complicated by the fact that we use the ACS-reported margins of error to compute Empirical Bayes shrunken versions of our key ACS measures. The shrunken measures help account for attenuation bias that results from the fact that smaller units' measures include more measurement error due to smaller sample sizes. Appendix B2 describes the problems of measurement error and attenuation bias in detail. Below we describe the steps we take to create our derived measures from the raw ACS data. Note that we do not compute standard errors or Empirical Bayes shrunken versions of state-level measures. State samples are sufficiently large as to not be concerned about measurement error due to small samples. Therefore, many of the steps described below only refer to district, county, and metropolitan area data.

Step 1: We download and clean the raw ACS data for each year and unit, saving the measures of interest along with their margins of error. We use data from the 2005-2009, 2006-2010, 2007-2011, 2008-2012, 2009-2013, 2010-2014, 2011-2015, 2012-2016, 2013-2017, 2014-

2018, and 2015-2019 samples. In Appendix B1 we provide a list of the raw ACS data tables we downloaded and use to compute each derived measure.

Step 2: Some of our derived measures require combining various fields from ACS in order to compute our desired metric. For example, in order to compute the proportion of adults with a bachelor's degree or higher we sum the number of men with a bachelor's degree, a master's degree or a professional degree with the number of women with a bachelor's degree, a master's degree or a professional degree and divide that sum by the total number of adults in the unit. Each of these component measures is reported with its own margin of error in the raw ACS data. We use the margins of error from each component measure to generate a single standard error for the combined bachelor's degree attainment rate variable (and do the same for all 6 socioeconomic measures that make up the SES composite). Appendix B3 describes our methodology for computing the sampling variance of sums of ACS variables in detail.

Step 3: After constructing the 6 SES measures and their standard errors we impute some missing data using Stata's –**mi impute chained**– routine, which fills in missing values iteratively by using chained equations. We reshape the data from long (one observation for each unit and race group [all, White, Black, Hispanic, Asian, and Native American] in each year) to wide (one observation for each unit and a separate variable for each of the 6 SES by race measures in each year). We use both the 6 SES measures and their standard errors in the imputation model as well as the total population count in each unit. The imputation model, therefore, includes median income, proportion of adults with a bachelor's degree or higher, child poverty rate, SNAP receipt rate, single mother headed household rate, and unemployment rate for each race group (all, White, Black, Hispanic, Asian, and Native American) in each of the 11-year spans for both the estimates and their standard errors.[22] We estimate the imputation model 5 times.

Step 4: Next, we use the imputed data to compute the SES composite. This is done 5 times for each imputed data set and then we take the average. This measure is computed as the first

[22] Our imputation method varies slightly for metropolitan statistical areas. An imputation model that includes a variable for each group and each year for each of the 6 measures is not feasible for metropolitan statistical areas because it results in more variables than units. Therefore, we impute the metropolitan area data separately by year and only use 5 years of surrounding data; e.g., we impute 2013-2017 data with 2011-2015, 2012-2016, 2013-2017, 2014-2018 and 2015-2019.

principal component score of the following measures (each standardized): median income, percent of adults ages 25 and older with a bachelor's degree or higher, child poverty rate, SNAP receipt rate, single mother headed household rate, and employment rate for adults ages 16-64. We use the logarithm of median income in these computations. We calculate the component loadings by conducting the analysis in 2008-2012 at the geographic school district level and weighting by geographic school district enrollment. We then use the loadings from this principal component analysis to calculate SES composite values for different subgroups, years and units. Note that only observations without any imputed ACS data are used in the computation of the factor weights.

Table 15 shows the component loadings for the socioeconomic status composite as well as the mean and standard deviation of each measure it includes. The "standardized loadings" indicate the coefficients used to compute the overall geographic school district SES composite score from the 6 standardized indicator variables in 2008-2012, resulting in an SES composite that has an enrollment-weighted mean of 0 and standard deviation of 1 across all geographic school districts in 2008-2012 without any imputed data. The "unstandardized loadings" are rescaled versions of the coefficients that are used to construct an SES composite score from the raw (unstandardized) indicator variables, but which is on the same scale as the standardized SES composite scores.

To provide context for interpreting values of the SES composite, Table 16 reports average values of the indicator variables at different values of the SES composite.

Step 5: The next step is to construct a standard error of the SES composite. We discuss our methodology in detail in Appendix B4.

Step 6: The final step is to do the Empirical Bayes shrinkage of the SES composites as well as for each of the 6 SES measures that go into making the composite. In addition to the time-varying versions of the SES composite, we also create an SES composite that is the average of SES in the 2005-2009, 2010-2014 and 2015-2019 ACS (i.e., using years of non-overlapping ACS samples). The shrinkage is done using a random effects meta-analysis regression model weighted by the standard error of each measure. Note that we use the same suppression rules described on page 36 to suppress SES estimates with large standard errors. We do not report group specific SES if the reliability of the all group estimate for a given geography is below .70. Furthermore, if either the White or Black/Hispanic/Asian/Native American group specific SES is censored by this first rule then we censor the SES gap between the two groups as well. See page 36 for more details of the censoring rules.

III.B. Common Core of Data Imputation

We use data derived from the CCD from the Longitudinal School Demographic Dataset (LSDD). Detailed documentation for that dataset is available upon request from sedasupport@stanford.edu. The dataset includes school-level data from the CCD from Fall 1991 to Fall 2021. The CCD is published by the National Center for Education Statistics and includes enrollment counts by race/ethnicity and free or reduced-price lunch eligibility. However, CCD enrollment data are missing in some cases and have data quality issues in others. To address these issues, the LSDD replaces missing and implausible race/ethnicity and free or reduced-price lunch enrollment data via multiple imputation. The imputation model included school-level data from 1991-1992 through 2021-2022 school years. The imputation model includes annual school-level total enrollment, enrollments by race, enrollments by free or reduced-price lunch status, as well as several auxiliary variables (school economic disadvantaged rate, child poverty rate in the school's census tract, percent of students direct-certified as free or reduced-price lunch, and Title 1 status) in years they are available. The imputation is run 10 times, and the values are averaged across datasets. More details are provided in the LSDD data documentation.

IV. Versioning and Publication

New or revised data will be posted periodically to the SEDA website. SEDA updates that contain substantially new information are labeled as a new version (e.g., V1.0, V2.0, etc.). Updates that make corrections or minor revisions to previously posted data are labeled as a subsidiary of the current version (e.g., V1.1, V1.2, etc.). When citing any SEDA data set for presentation, publication or use in the field, please include the version number in the citation. All versions of the data will remain archived and available on the SEDA website to facilitate data verification and research replication.

SEDA 5.0 makes the following additions to data contained in SEDA 4.1:

- Test score and covariate estimates for administrative school districts.
- Test score and covariate estimates including data from the 2018-2019 school year.

SEDA 5.0 makes the following modifications to the procedures used in SEDA 4.1:

- A revised crosswalk.
- An updated file of test reliabilities.
- Additional pre- and post-estimation data removals to improve data quality.
- Removal of the multiracial subgroup mean estimates and the White-multiracial gap estimates due to concerns about data quality.

References

Reardon, S. F., Fahle, E. M., Kalogrides, D., Podolsky, A., & Zárate, R. C. (2019). Gender Achievement Gaps in U.S. School Districts. *American Educational Research Journal*, 000283121984382. https://doi.org/10.3102/0002831219843824

Reardon, S. F., Kalogrides, D., & Ho, A. D. (2019). 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*, 107699861987408. http://doi.org/10.3102/1076998619874089

Reardon, S. F., Kalogrides, D., Fahle, E. M., Podolsky, A., & Zárate, R. C. (2018). The relationship between test item format and gender achievement gaps on math and ELA tests in fourth and eighth grades. Educational Researcher, 1–11. https://doi.org/10.3102/0013189X18762105

Reardon, S.F., Papay, J.P., Kilbride, T., Strunk, K.O., Cowen, J., An, L., & Donohue, K. (2019). Can Repeated Aggregate Cross-Sectional Data Be Used to Measure Average Student Learning Rates? A Validation Study of Learning Rate Measures in the Stanford Education Data Archive. (CEPA Working Paper No.19-08). Retrieved from Stanford Center for Education Policy Analysis: http://cepa.stanford.edu/wp19-08

Reardon, S. F., Shear, B. R., Castellano, K. E., & Ho, A. D. (2017). Using heteroskedastic ordered probit models to recover moments of continuous test score distributions from coarsened data. *Journal of Educational and Behavioral Statistics*, 42(1), 3–45. https://doi.org/10.3102/1076998616666279

Reardon, S. F., Kalogrides, D., & Ho, A. D. (2019). 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*, 107699861987408. http://doi.org/10.3102/1076998619874089

Shear, B. R., & Reardon, S. F. (2021). Using Pooled Heteroskedastic Ordered Probit Models to Improve Small-Sample Estimates of Latent Test Score Distributions. *Journal of Educational and Behavioral Statistics*, *46*(1), 3–33. https://doi.org/10.3102/1076998620922919

Tables

Table 1. Test Score Files

File Name	Form	Metric	Test Score Estimations: Means and Achievement Gaps																
			Unit							Disaggregated by			Subgroups						
													Means				Gaps		
			School	Geo District	Admin District	County	Metro	Comm Zone	State	Year	Grade	Subject	All	Race	Gender	ECD	Race	Gender	ECD
seda_school_pool_cs_5.0	Pooled	CS	X										X						
seda_school_pool_gcs_5.0	Pooled	GCS	X										X						
seda_geodist_long_cs_5.0	Long	CS		X						X	X	X	X	X	X	X	X	X	X
seda_geodist_long_gcs_5.0	Long	GCS		X						X	X	X	X	X	X	X	X	X	X
seda_geodist_poolsub_cs_5.0	Pooled	CS		X								X	X	X	X	X	X	X	X
seda_geodist_poolsub_gcs_5.0	Pooled	GCS		X								X	X	X	X	X	X	X	X
seda_geodist_pool_gcs_5.0	Pooled	CS		X									X	X	X	X	X	X	X
seda_geodist_pool_cs_5.0	Pooled	GCS		X									X	X	X	X	X	X	X
seda_admindist_long_cs_5.0	Long	CS			X					X	X	X	X	X	X	X	X	X	X
seda_admindist_long_gcs_5.0	Long	GCS			X					X	X	X	X	X	X	X	X	X	X
seda_admindist_poolsub_cs_5.0	Pooled	CS			X							X	X	X	X	X	X	X	X
seda_admindist_poolsub_gcs_5.0	Pooled	GCS			X							X	X	X	X	X	X	X	X
seda_admindist_pool_gcs_5.0	Pooled	CS			X								X	X	X	X	X	X	X
seda_admindist_pool_cs_5.0	Pooled	GCS			X								X	X	X	X	X	X	X
seda_county_long_cs_5.0	Long	CS				X				X	X	X	X	X	X	X	X	X	X
seda_county_long_gcs_5.0	Long	GCS				X				X	X	X	X	X	X	X	X	X	X
seda_county_poolsub_cs_5.0	Pooled	CS				X						X	X	X	X	X	X	X	X
seda_county_poolsub_gcs_5.0	Pooled	GCS				X						X	X	X	X	X	X	X	X
seda_county_pool_cs_5.0	Pooled	CS				X							X	X	X	X	X	X	X
seda_county_pool_gcs_5.0	Pooled	GCS				X							X	X	X	X	X	X	X
seda_metro_long_cs_5.0	Long	CS					X			X	X	X	X	X	X	X	X	X	X
seda_metro_long_gcs_5.0	Long	GCS					X			X	X	X	X	X	X	X	X	X	X
seda_metro_poolsub_cs_5.0	Pooled	CS					X					X	X	X	X	X	X	X	X
seda_metro_poolsub_gcs_5.0	Pooled	GCS					X					X	X	X	X	X	X	X	X
seda_metro_pool_cs_5.0	Pooled	CS					X						X	X	X	X	X	X	X
seda_metro_pool_gcs_5.0	Pooled	GCS					X						X	X	X	X	X	X	X
seda_commzone_long_cs_5.0	Long	CS						X		X	X	X	X	X	X	X	X	X	X
seda_commzone_long_gcs_5.0	Long	GCS						X		X	X	X	X	X	X	X	X	X	X
seda_commzone_poolsub_cs_5.0	Pooled	CS						X				X	X	X	X	X	X	X	X
seda_commzone_poolsub_gcs_5.0	Pooled	GCS						X				X	X	X	X	X	X	X	X
seda_commzone_pool_cs_5.0	Pooled	CS						X					X	X	X	X	X	X	X
seda_commzone_pool_gcs_5.0	Pooled	GCS						X					X	X	X	X	X	X	X
seda_state_long_cs_5.0	Long	CS							X	X	X	X	X	X	X	X	X	X	X
seda_state_long_gcs_5.0	Long	GCS							X	X	X	X	X	X	X	X	X	X	X
seda_state_poolsub_cs_5.0	Pooled	CS							X			X	X	X	X	X	X	X	X
seda_state_poolsub_gcs_5.0	Pooled	GCS							X			X	X	X	X	X	X	X	X
seda_state_pool_cs_5.0	Pooled	CS							X				X	X	X	X	X	X	X
seda_state_pool_gcs_5.0	Pooled	GCS							X				X	X	X	X	X	X	X

Notes:

Metric:	CS = Cohort Scale; GCS = Grade Scale
Unit	*Geodist = Geographically Defined School District; Admindist = Administrative School District; Metro = Metropolitan Statistical Area; Commzone = Commuting Zone*
Academic Years:	2008/09 – 2018/19
Grades:	3 – 8
Subjects:	Math, RLA
Race:	Asian, Black, Hispanic, Native American, White
Race Gaps:	White-Asian, White-Black, White-Hispanic, White-Native American
Gender:	male, female
Gender Gaps:	male-female
ECD:	economically disadvantaged, not disadvantaged (as defined by states)
ECD Gaps:	not disadvantaged-economically disadvantaged

Table 2. Covariate Data Files

Covariate Data				
		Disaggregated by		
File Name	Form	Unit	Year	Grade
seda_cov_school_pool_5.0	Pooled	X		
seda_cov_school_annual_5.0	Pooled	X	X	
seda_cov_geodist_long_5.0	Long	X	X	X
seda_cov_geodist_annual_5.0	Pooled	X	X	
seda_cov_geodist_pool_5.0	Pooled	X		
seda_cov_admindist_long_5.0	Long	X	X	X
seda_cov_admindist_annual_5.0	Pooled	X	X	
seda_cov_admindist_pool_5.0	Pooled	X		
seda_cov_county_long_5.0	Long	X	X	X
seda_cov_county_annual_5.0	Pooled	X	X	
seda_cov_county_pool_5.0	Pooled	X		
seda_cov_metro_long_5.0	Long	X	X	X
seda_cov_metro_annual_5.0	Pooled	X	X	
seda_cov_metro_pool_5.0	Pooled	X		
seda_cov_state_long_5.0	Long	X	X	X
seda_cov_state_annual_5.0	Pooled	X	X	
seda_cov_state_pool_5.0	Pooled	X		

Table 3. Example ED*Facts* Data Structure

FIPS	NCESSCH	Subgroup	Subject	Grade	Year	Number of students scoring at…			
						Level 1	Level 2	Level 3	Level 4
99	997777755555	All Students	Math	3	2009	26	87	185	32
99	997777755555	All Students	RLA	3	2009	13	102	195	20
99	997777755556	All Students	Math	3	2009	35	238	192	7
99	997777755556	All Students	RLA	3	2009	7	278	187	0

Note. The data shown in this table are not real.

Table 4a. Availability of SEDA Estimates by State-Subject-Year-Grade

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Alabama																																																																			
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Alaska																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X																								
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X																								
Arizona																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Arkansas																																																																		
Math	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
California																																																																		
Math	X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X									X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Colorado																																																																		
Math																			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X				X	X	X				X	X	X				X	X	X	X			X	X	X	X		
RLA																			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X				X	X	X				X	X	X				X	X	X	X			X	X	X	X		
Connecticut																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Delaware																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
DC																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X	X	X	X			X	X	X				X	X	X	X	X							
RLA	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X				X	X	X	X	X	X	X	X	X	X	X	X
Florida																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X								X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X		
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Georgia																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Table 4a. Availability of SEDA Estimates by State-Subject-Year-Grade (Continued)

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Hawaii																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Idaho																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Illinois																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Indiana																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Iowa																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Kansas																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Kentucky																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Louisiana																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Maine																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Maryland																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X			X	X	X	X	X			X	X	X	X			X	X	X	X									X	X	X	X		
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X
Massachusetts																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Table 4a. Availability of SEDA Estimates by State-Subject-Year-Grade (Continued)

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Michigan																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Minnesota																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Mississippi																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Missouri																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Montana																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X													X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X													X	X	X	X	X	X				X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Nebraska																																																																		
Math													X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Nevada																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X													X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X												X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
New Hampshire																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
New Jersey																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X						X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X						X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
New Mexico																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X				X	X	X	X								
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X												
New York																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X																																	
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X																															

Table 4a. Availability of SEDA Estimates by State-Subject-Year-Grade (Continued)

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
North Carolina																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
North Dakota																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Ohio																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X		X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X		
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Oklahoma																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Oregon																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X					X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X		X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Pennsylvania																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Rhode Island																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X				X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X				X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
South Carolina																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
South Dakota																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Tennessee																																																																		
Math	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X								X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Texas																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X		
RLA			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X			X	X	X	X

Table 4a. Availability of SEDA Estimates by State-Subject-Year-Grade (Continued)

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Utah																																																																		
Math	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X				X	X	X				X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			X	X	X				X	X	X	X	X	X
Vermont																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X												
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X												
Virginia																																																																		
Math	X	X					X	X					X	X					X	X					X	X					X	X					X	X					X	X					X	X	X	X									X	X	X	X		
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Washington																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X								X	X				X	X	X	X			X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X				X	X	X	X			X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X
West Virginia																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X						
Wisconsin																																																																		
Math	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Wyoming																																																																		
Math	X	X	X	X	X	X							X	X	X	X	X	X													X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RLA	X	X	X	X	X	X							X	X	X	X	X	X							X	X	X	X	X	X							X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Table 4b. Reason for Unavailability of SEDA Estimates by State-Subject-Year-Grade

Legend 1 Not available in EDFacts 2 < 94% or > 105% participation 3 Different tests 4 Different counts 5 Insufficient Data

	2009						2010						2011						2012						2013						2014					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Alaska																																				
Math																																				
RLA																																				
Arizona																																				
Math																																				
RLA																																				
Arkansas																																				
Math						3						3																								
RLA																																				
California																																				
Math					3	3					3	3					3	3					3	3					3	3	2	2	2	2	2	2
RLA																															2	2	2	2	2	2
Colorado																																				
Math	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5																		
RLA	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5																		
Connecticut																																				
Math																															2	2	2	2	2	2
RLA																															2	2	2	2	2	2
DC																																				
Math																																				
RLA													4																							
Florida																																				
Math																														3	2	2	2	2	2	2
RLA																																				
Idaho																																				
Math																															2	2	2	2	2	2
RLA																															2	2	2	2	2	2
Kansas																																				
Math																															1	1	1	1	1	1
RLA																															1	1	1	1	1	1

	2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Alaska																														
Math							1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
RLA							1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Arizona																														
Math												3						3						3						3
RLA																														
Arkansas																														
Math						3																								
RLA																														
California																														
Math																														
RLA																														
Colorado																														
Math				2	2	2				2	2	2				2	2	2					2	2					2	2
RLA				2	2	2				2	2	2				2	2	2					2	2					2	2
Connecticut																														
Math																														
RLA																														
DC																														
Math					3	3					3	3				2	2	2						3	3	3	3	3	3	3
RLA																2	2	2												
Florida																														
Math					3	3					3	3					3	3					3	3					3	3
RLA																														
Idaho																														
Math																														
RLA																														
Kansas																														
Math																														
RLA																														

Table 4b. Reason for Unavailability of SEDA Estimates by State-Subject-Year-Grade (Continued)

Legend 1 Not available in EDFacts 2 < 94% or > 105% participation 3 Different tests 4 Different counts 5 Insufficient Data

	2009						2010						2011						2012						2013						2014						2015						2016						2017						2018						2019					
	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8	3	4	5	6	7	8
Maine																																																																		
Math																																										2																								
RLA																																									2	2																								
Maryland																																																																		
Math																															2	2		2	2						3	3					3	3					3	3	1	1	1	1	1	1					3	3
RLA																															2	2		2	2																				1	1	1	1	1	1						
Massachusetts																																																																		
Math																																					3	3	3	3	3	3																								
RLA																																					3	3	3	3	3	3																								
Missouri																																																																		
Math																														3						3						3						3						2						3						3
RLA																																																																		
Montana																																																																		
Math																															2	2	2	2	2	2	2	2	2	2	2	2																								
RLA																															2	2	2	2	2	2	2	2	2	2	2	2							2	2	2															
Nebraska																																																																		
Math	3	3	3	3	3	3	3	3	3	3	3	3																																																						
RLA	3	3	3	3	3	3																																																												
Nevada																																																																		
Math																															2	2	2	2	2	2	1	1	1	1	1	1																								
RLA																																2	2	2	2	2	1	1	1	1	1	1																								
New Jersey																																																																		
Math																																						2	2	2	2	2						2						3						3						3
RLA																																						2	2	2	2	2						2																		
New Mexico																																																																		
Math																																																4				1	1	4					4	4	4	4	4	4	4	4
RLA																																																							1	1	1	1	1	1	4	4	4	4	4	4
New York																																																																		
Math																																		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
RLA																																				2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

Table 4b. Reason for Unavailability of SEDA Estimates by State-Subject-Year-Grade (Continued)

Legend 1 Not available in EDFacts 2 < 94% or > 105% participation 3 Different tests 4 Different counts 5 Insufficient Data

	2009						2010						2011						2012						2013						2014					
	3	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**
North Dakota																																				
Math																																				
RLA																																				
Ohio																																				
Math																															3	3	3	3	3	3
RLA																															3	3	3	3	3	3
Oklahoma																																				
Math																								3						3						
RLA																																				
Oregon																																				
Math																															2	2	2	2		2
RLA																															2		2		2	
Rhode Island																																				
Math																																				
RLA																																				
South Dakota																																				
Math																															2	2	2	2	2	2
RLA																															2	2	2	2	2	2
Tennessee																																				
Math						3						3						3						3						3						3
RLA																																				
Texas																																				
Math																							3	3					3	3					3	3
RLA	3	3					3	3					3	3					3	3					3	3					3	3				
Utah																																				
Math						3						3						3						3						3						
RLA																																				
Vermont																																				
Math																																				
RLA																																				

	2015						2016						2017						2018						2019					
	3	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**
North Dakota																														
Math	4	4	2	2	2	2																								
RLA	4	4	2	2	2	2																								
Ohio																														
Math						3					3	3					3	3					3	3					3	3
RLA																														
Oklahoma																														
Math																														
RLA																														
Oregon																														
Math																		2						2						
RLA																														
Rhode Island																														
Math				2	2	2																								
RLA				2	2	2																								
South Dakota																														
Math																														
RLA																														
Tennessee																														
Math						3	5	5	5	5	5	2						3						3						3
RLA							5	5	5	5	5	2																		
Texas																														
Math					3	3					3	3					3	3					3	3					3	3
RLA	3	3					3	3					3	3					3	3					3	3				
Utah																														
Math												2				2	2	2				2	2	2						
RLA																	2	2				2	2	2						
Vermont																														
Math																			1	1	1	1	1	1	1	1	1	1	1	1
RLA																			1	1	1	1	1	1	1	1	1	1	1	1

Table 4b. Reason for Unavailability of SEDA Estimates by State-Subject-Year-Grade (Continued)

Legend 1 Not available in EDFacts 2 < 94% or > 105% participation 3 Different tests 4 Different counts 5 Insufficient Data

	2009						2010						2011						2012					
	3	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**
Virginia																								
Math			3	3	3	3			3	3	3	3			3	3	3	3			3	3	3	3
RLA																								
Washington																								
Math																								
RLA																								
West Virginia																								
Math																								
RLA																								
Wyoming																								
Math							1	1	1	1	1	1							4	4	4	4	4	4
RLA							1	1	1	1	1	1							4	4	4	4	4	4

	2013						2014						2015						2016					
	3	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**
Virginia																								
Math			3	3	3	3			3	3	3	3			3	3	3	3			3	3	3	3
RLA																								
Washington																								
Math							2	2	2	2	2	2	2			2	2	2					2	2
RLA							2	2	2	2	2	2				2	2	2					2	2
West Virginia																								
Math							2	2	2	2	2	4												
RLA																								
Wyoming																								
Math	2	2	2	2	2	2						2												
RLA							2	2	2	2	2	2												

	2017						2018						2019					
	3	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**	**3**	**4**	**5**	**6**	**7**	**8**
Virginia																		
Math					3	3	1	1	1	1	1	1					3	3
RLA																		
Washington																		
Math						2												
RLA						2												
West Virginia																		
Math																		
RLA													1	1	1	1	1	1
Wyoming																		
Math																		
RLA																		

Table 5. Double Counting of Bureau of Indian Education Schools

NCESSCH Dropped from ED*Facts*	School Name	NCESSCH Kept in SEDA	Note
590002500172	TURTLE MOUNTAIN COMMUNITY MIDDLE SCHOOL	380253000751	CCD Task Force
590010600170	TURTLE MOUNTAIN COMMUNITY ELEMENTARY SCHOOL	380253000750	CCD Task Force
590007700173	TWIN BUTTES ELEMENTARY SCHOOL	381860000757	CCD Task Force
590011700174	WHITE SHIELD ELEMENTARY SCHOOL	381968000807	CCD Task Force
590018700086	NAH TAH WAHSH PUBLIC SCHOOL ACADEMY	260010300646	CCD Task Force
590005400080	JOSEPH K LUMSDEN BAHWETING ANISHNABE ACADEMY	260007100492	CCD Task Force
590018900167	MANDAREE ELEMENTARY SCHOOL	381185000747	SEDA Team
590018900167	MANDAREE HIGH SCHOOL	381185000006	SEDA Team
230006400664	INDIAN TOWNSHIP SCHOOL	590004200052	SEDA Team
370015302953	CHEROKEE ELEMENTARY	590006600044	SEDA Team
370015303150	CHEROKEE MIDDLE SCHOOL	590010100045	SEDA Team
230006900630	BEATRICE RAFFERTY SCHOOL	590013700042	SEDA Team
230006600671	INDIAN ISLAND SCHOOL	590016000051	SEDA Team

Note. CCD Task Force indicates the school was listed in the CCD's Documentation (Double Counting of Bureau of Indian Education Schools). SEDA Team indicates that it was determined by looking at school coordinates, assessments received by grade, and school contact information since the CCD task force only began with SY 2009-10.

Table 6. NAEP Means and Standard Deviations by Year and Grade.

	Grade	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
								Math						
Means	3	227.8	227.9	227.9	228.4	227.9	228.8	229.6	228.9	228.1	227.5	226.9	227.2	227.5
	4	237.9	238.2	238.5	239.0	238.5	239.3	240.1	239.2	238.4	237.9	237.5	237.6	237.8
	5	248.0	248.5	249.1	249.6	249.1	249.8	250.5	249.6	248.7	248.4	248.1	248.0	248.0
	6	258.1	258.9	259.6	260.2	259.7	260.3	260.9	260.0	259.1	258.9	258.6	258.5	258.3
	7	268.3	269.2	270.2	270.9	270.3	270.8	271.3	270.4	269.4	269.3	269.2	268.9	268.6
	8	278.4	279.6	280.8	281.5	280.9	281.3	281.8	280.8	279.7	279.8	279.8	279.3	278.9
SDs	3	27.0	26.9	26.9	27.1	27.2	27.5	27.8	27.9	28.0	28.9	29.8	30.1	30.4
	4	28.9	28.8	28.7	28.9	28.9	29.2	29.4	29.5	29.6	30.6	31.5	31.9	32.2
	5	30.7	30.7	30.6	30.6	30.6	30.9	31.1	31.2	31.3	32.2	33.2	33.6	34.0
	6	32.6	32.5	32.4	32.4	32.4	32.5	32.7	32.9	33.0	33.9	34.8	35.4	35.9
	7	34.5	34.4	34.2	34.2	34.1	34.2	34.3	34.5	34.7	35.6	36.5	37.1	37.7
	8	36.4	36.2	36.1	36.0	35.8	35.9	36.0	36.2	36.3	37.3	38.2	38.8	39.5
								RLA						
Means	3	206.4	206.5	206.6	206.8	207.0	207.6	208.2	209.2	210.1	209.5	208.8	208.2	207.6
	4	216.9	217.2	217.5	217.8	218.2	218.9	219.6	220.2	220.9	220.4	219.9	219.1	218.3
	5	227.4	227.9	228.3	228.9	229.4	230.2	231.0	231.3	231.6	231.3	230.9	230.0	229.0
	6	238.0	238.6	239.2	239.9	240.5	241.4	242.3	242.3	242.3	242.2	242.0	240.8	239.6
	7	248.5	249.3	250.1	250.9	251.7	252.7	253.7	253.4	253.1	253.1	253.1	251.7	250.3
	8	259.1	260.0	260.9	261.9	262.9	264.0	265.1	264.5	263.8	264.0	264.1	262.5	261.0
SDs	3	38.2	37.8	37.5	37.7	37.8	38.2	38.6	38.3	38.0	38.6	39.2	39.5	39.7
	4	37.7	37.4	37.0	37.1	37.2	37.5	37.8	37.6	37.4	38.0	38.6	39.1	39.5
	5	37.3	36.9	36.5	36.5	36.6	36.8	37.0	36.9	36.7	37.4	38.1	38.7	39.3
	6	36.8	36.4	36.0	36.0	36.0	36.1	36.2	36.2	36.1	36.8	37.5	38.3	39.1
	7	36.4	35.9	35.4	35.4	35.4	35.4	35.4	35.4	35.5	36.2	36.9	37.9	38.9
	8	35.9	35.4	34.9	34.9	34.8	34.7	34.6	34.7	34.8	35.6	36.3	37.5	38.7

Note. We use the expanded population estimates, which may differ slightly from those reported publicly on the website.

Table 7a. SBAC States and Years Used to Create BIE Waiver Cutscores

	2014	2015	2016	2017	2018	2019
California		X	X	X	X	X
Connecticut		X	X	X	X	X
Delaware		X	X	X	X	X
Hawaii	X	X	X	X	X	X
Idaho		X	X	X	X	X
Maine		X				
Michigan		X	X	X		
Missouri		X				
Montana		X	X	X	X	X
Nevada		X	X	X		
New Hampshire		X	X	X	X	X
North Dakota		X	X	X		
Oregon		X	X	X	X	X
South Dakota		X	X	X	X	X
Vermont		X	X	X		
Washington		X	X	X	X	X
West Virginia		X	X	X	X	

Table 7b. PARCC States and Years Used to Create BIE Waiver Cutscores

	2014	2015	2016	2017	2018	2019
Colorado		X	X	X		
DC		X	X	X	X	X
Illinois		X	X	X	X	
Maryland		X	X	X	X	X
Mississippi		X				
New Jersey		X	X	X	X	X
New Mexico					X	
Rhode Island		X	X	X		

Table 8. BIE Schools Dropped from SEDA

State Abbreviation	Year	NCES School ID	School Name
MS	2016	590005300056	Standing Pine Elementary School
MS	2017	590005300056	Standing Pine Elementary School
MS	2016	590007800048	Choctaw Central Middle School
MS	2017	590007800048	Choctaw Central Middle School
MS	2016	590010000057	Tucker Elementary School
MS	2017	590010000057	Tucker Elementary School
MS	2016	590011100050	Conehatta Elementary School
MS	2017	590011100050	Conehatta Elementary School
MS	2016	590012300054	Pearl River Elementary School
MS	2017	590012300054	Pearl River Elementary School
MS	2016	590017200055	Red Water Elementary School
MS	2017	590017200055	Red Water Elementary School
MS	2016	590019400043	Bogue Chitto Elementary School
MS	2017	590019400043	Bogue Chitto Elementary School
WI	2012	590010400087	Lac Courte Oreilles Ojibwa School
WI	2012	590011400090	Oneida Nation School
WI	2012	590014400088	Menominee Tribal School

Note. Year indicates the spring of the school year.

Table 9. Subject-Grade-Year Cases Removed Pre-Estimation

	sedaadmin		sedacounty		sedacz		sedafips		sedalea		sedametro	
Only 1 testscore	1,124,572	7.99%	186,451	5.56%	23,909	2.74%	87	0.13%	914,290	7.65%	30,874	2.64%
All participation < 95%	506,096	3.59%	49,050	1.46%	13,414	1.54%	950	1.45%	324,495	2.72%	17,733	1.52%
Subgroup participation < 95%	190,528	1.35%	37,670	1.12%	10,524	1.21%	607	0.93%	156,752	1.31%	15,268	1.31%
Representation < 95%	72,207	0.51%	15,781	0.47%	3,809	0.44%	255	0.39%	51,516	0.43%	7,970	0.68%
Alternative assessments > 40%	47,457	0.34%	54	0.00%		0.00%		0.00%	1,179	0.01%		0.00%
No sufficient cells	217,555	1.55%	35,336	1.05%	5,878	0.67%	346	0.53%	159,461	1.33%	7,896	0.68%
Missing all subgroup	60	0.00%		0.00%		0.00%		0.00%		0.00%		0.00%
Not dropped	11,920,791	84.67%	3,029,477	90.33%	814,674	93.40%	63,184	96.57%	10,341,924	86.55%	1,088,451	93.17%
Total	14,079,266	100.00%	3,353,819	100.00%	872,208	100.00%	65,429	100.00%	11,949,617	100.00%	1,168,192	100.00%

Table 10. Grade Spans of Test Score Estimates by School

	High Grade					
	3	4	5	6	7	8
Low Grade						
3	1,378	3,374	27,157	13,677	849	11,136
4		28	303	453	79	710
5			70	522	126	2,759
6				203	153	13,402
7					89	5,314
8						921

Table 11a. State Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)
CS Scale	all	0.02388	0.00028	-0.00067	0.02838	0.00029	-0.00067	0.02158	0.00035	-0.00079
	asn	0.07022	0.00043	0.00178	0.08257	0.00059	0.00371	0.06332	0.00047	0.00037
	blk	0.01986	0.00038	-0.00015	0.02249	0.00042	0.00009	0.01926	0.00046	-0.00039
	ecd	0.01094	0.00043	-0.00097	0.01354	0.00040	-0.00096	0.01090	0.00054	-0.00110
	fem	0.02159	0.00028	-0.00061	0.02435	0.00030	-0.00062	0.02133	0.00036	-0.00063
	hsp	0.01481	0.00056	-0.00054	0.01675	0.00048	-0.00025	0.01546	0.00073	-0.00086
	mal	0.02739	0.00030	-0.00077	0.03314	0.00032	-0.00075	0.02403	0.00040	-0.00089
	mfg	0.00226	0.00005	0.00001	0.00195	0.00004	-0.00009	0.00373	0.00009	0.00018
	nam	0.06124	0.00048	-0.00245	0.05691	0.00047	-0.00148	0.06860	0.00061	-0.00359
	nec	0.01027	0.00025	-0.00024	0.01387	0.00033	-0.00024	0.00921	0.00032	-0.00034
	neg	0.00840	0.00016	-0.00009	0.00917	0.00014	-0.00004	0.00863	0.00022	-0.00015
	wag	0.07038	0.00035	0.00216	0.08279	0.00040	0.00293	0.06242	0.00038	0.00172
	wbg	0.03352	0.00018	0.00099	0.03392	0.00022	0.00096	0.03473	0.00019	0.00105
	whg	0.03597	0.00024	0.00115	0.03648	0.00021	0.00118	0.03754	0.00033	0.00107
	wht	0.02652	0.00028	0.00038	0.03020	0.00034	0.00079	0.02567	0.00032	-0.00001
	wng	0.06983	0.00018	0.00070	0.07024	0.00022	0.00168	0.07125	0.00019	-0.00013
GCS Scale	all	0.25330	0.00298	0.00034	0.29083	0.00323	0.01265	0.24351	0.00422	-0.01109
	asn	0.73834	0.00624	0.03685	0.83996	0.01358	0.08920	0.71689	0.00541	-0.00286
	blk	0.21184	0.00401	0.00437	0.22821	0.00515	0.01628	0.21809	0.00533	-0.00663
	ecd	0.11559	0.00412	-0.00671	0.13727	0.00317	0.00001	0.12367	0.00637	-0.01356
	fem	0.22981	0.00302	0.00007	0.24999	0.00318	0.01053	0.24060	0.00421	-0.00925
	hsp	0.15758	0.00586	-0.00136	0.17012	0.00502	0.00906	0.17486	0.00851	-0.01153
	mal	0.29059	0.00325	0.00043	0.33971	0.00361	0.01501	0.27126	0.00475	-0.01257
	mfg	0.02446	0.00048	0.00052	0.01960	0.00033	0.00042	0.04204	0.00100	0.00163
	nam	0.64711	0.00434	-0.01141	0.57050	0.00495	0.02136	0.77767	0.00783	-0.04846
	nec	0.10914	0.00281	0.00076	0.14273	0.00325	0.00698	0.10414	0.00379	-0.00486
	neg	0.08823	0.00158	0.00131	0.09071	0.00160	0.00517	0.09774	0.00257	-0.00262
	wag	0.74371	0.00563	0.04334	0.84195	0.01083	0.08147	0.70484	0.00405	0.01275
	wbg	0.35685	0.00238	0.01807	0.34475	0.00473	0.03124	0.39135	0.00193	0.00793
	whg	0.38567	0.00340	0.02212	0.37289	0.00498	0.03504	0.42253	0.00353	0.00772
	wht	0.27974	0.00342	0.01081	0.30835	0.00550	0.02722	0.28997	0.00362	-0.00301
	wng	0.74219	0.00278	0.02558	0.71120	0.00681	0.06035	0.80617	0.00223	-0.00905

Table 11b. Commuting Zone Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)
CS Scale	all	0.04079	0.00057	-0.00054	0.04392	0.00075	-0.00009	0.04219	0.00056	-0.00088
	asn	0.08540	0.00127	0.00012	0.09952	0.00151	0.00171	0.07868	0.00128	-0.00074
	blk	0.03277	0.00076	0.00055	0.03547	0.00095	0.00088	0.03363	0.00072	0.00041
	ecd	0.02938	0.00063	-0.00096	0.03221	0.00074	-0.00054	0.03133	0.00065	-0.00134
	fem	0.03747	0.00056	-0.00036	0.03853	0.00073	0.00000	0.04185	0.00056	-0.00056
	hsp	0.02182	0.00078	-0.00120	0.02423	0.00090	-0.00076	0.02454	0.00084	-0.00154
	mal	0.04481	0.00059	-0.00074	0.05003	0.00077	-0.00029	0.04369	0.00059	-0.00107
	mfg	0.00249	0.00006	0.00000	0.00236	0.00004	-0.00008	0.00391	0.00010	0.00018
	nam	0.05929	0.00102	-0.00190	0.05720	0.00121	-0.00119	0.06560	0.00101	-0.00269
	nec	0.02391	0.00065	-0.00049	0.02799	0.00085	-0.00042	0.02417	0.00064	-0.00041
	neg	0.02033	0.00025	0.00027	0.02185	0.00029	0.00058	0.01979	0.00028	-0.00003
	wag	0.07617	0.00078	0.00066	0.08801	0.00084	0.00168	0.06829	0.00085	0.00003
	wbg	0.04153	0.00037	0.00097	0.04373	0.00053	0.00175	0.04124	0.00032	0.00031
	whg	0.03354	0.00026	0.00040	0.03468	0.00034	0.00116	0.03511	0.00029	-0.00044
	wht	0.02387	0.00050	-0.00001	0.03123	0.00075	0.00027	0.02039	0.00046	-0.00017
	wng	0.06603	0.00059	0.00089	0.06670	0.00081	0.00222	0.06741	0.00050	-0.00022
GCS Scale	all	0.43108	0.00623	0.00601	0.44643	0.00909	0.02813	0.47620	0.00660	-0.01406
	asn	0.89005	0.01448	0.02650	1.01122	0.02068	0.08197	0.88940	0.01479	-0.01671
	blk	0.34616	0.00825	0.01539	0.36034	0.01153	0.03271	0.37924	0.00811	0.00103
	ecd	0.30928	0.00639	-0.00172	0.32613	0.00786	0.01615	0.35381	0.00775	-0.01817
	fem	0.39683	0.00624	0.00678	0.39255	0.00881	0.02578	0.47204	0.00657	-0.01033
	hsp	0.22900	0.00787	-0.00626	0.24349	0.00873	0.00937	0.27698	0.00988	-0.01987
	mal	0.47210	0.00643	0.00531	0.50752	0.00927	0.03009	0.49343	0.00698	-0.01656
	mfg	0.02704	0.00058	0.00070	0.02364	0.00044	0.00085	0.04402	0.00106	0.00164
	nam	0.62212	0.00995	-0.00538	0.57285	0.01220	0.02509	0.74410	0.01229	-0.03792
	nec	0.25233	0.00708	0.00191	0.28310	0.00892	0.01498	0.27340	0.00740	-0.00710
	neg	0.21514	0.00288	0.00829	0.22141	0.00435	0.01989	0.22363	0.00320	-0.00245
	wag	0.79869	0.00918	0.03111	0.89827	0.01372	0.07377	0.77108	0.00960	-0.00677
	wbg	0.44006	0.00478	0.02137	0.44347	0.00883	0.04547	0.46615	0.00358	-0.00103
	whg	0.35590	0.00325	0.01371	0.35404	0.00617	0.03445	0.39665	0.00335	-0.00875
	wht	0.25073	0.00578	0.00749	0.31846	0.00903	0.02390	0.23058	0.00532	-0.00410
	wng	0.69682	0.00695	0.02757	0.67652	0.01284	0.06431	0.76286	0.00584	-0.01004

Table 11c. Metropolitan Area Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)
CS Scale	all	0.04227	0.00068	0.00001	0.04845	0.00091	0.00037	0.04092	0.00066	-0.00026
	asn	0.09314	0.00134	0.00097	0.10758	0.00158	0.00244	0.08650	0.00134	0.00008
	blk	0.03842	0.00096	0.00070	0.04224	0.00124	0.00107	0.03887	0.00089	0.00044
	ecd	0.02517	0.00077	-0.00094	0.03072	0.00095	-0.00072	0.02457	0.00081	-0.00112
	fem	0.03976	0.00069	0.00015	0.04349	0.00091	0.00043	0.04165	0.00069	0.00002
	hsp	0.03079	0.00097	-0.00133	0.03372	0.00113	-0.00089	0.03398	0.00104	-0.00175
	mal	0.04595	0.00070	-0.00015	0.05432	0.00094	0.00033	0.04220	0.00069	-0.00047
	mfg	0.00229	0.00006	0.00001	0.00226	0.00005	-0.00006	0.00377	0.00009	0.00020
	nam	0.05434	0.00122	-0.00130	0.05555	0.00144	-0.00107	0.05641	0.00123	-0.00158
	nec	0.02971	0.00071	0.00038	0.03733	0.00096	0.00044	0.02683	0.00068	0.00043
	neg	0.01986	0.00029	0.00028	0.02149	0.00034	0.00063	0.01932	0.00032	-0.00009
	wag	0.07181	0.00081	0.00155	0.08136	0.00090	0.00246	0.06649	0.00083	0.00094
	wbg	0.04603	0.00045	0.00130	0.04843	0.00061	0.00203	0.04554	0.00039	0.00070
	whg	0.04187	0.00036	0.00065	0.04215	0.00043	0.00156	0.04444	0.00040	-0.00046
	wht	0.03425	0.00066	0.00022	0.04264	0.00094	0.00047	0.03022	0.00061	0.00002
	wng	0.05330	0.00074	0.00140	0.05385	0.00094	0.00226	0.05410	0.00057	0.00067
GCS Scale	all	0.44703	0.00766	0.01273	0.49358	0.01127	0.03599	0.46113	0.00769	-0.00688
	asn	0.97320	0.01565	0.03774	1.09364	0.02252	0.09429	0.97765	0.01528	-0.00843
	blk	0.40475	0.01042	0.01844	0.42805	0.01473	0.03871	0.43918	0.01004	0.00068
	ecd	0.26377	0.00788	-0.00208	0.30980	0.00947	0.01364	0.27717	0.00951	-0.01507
	fem	0.42097	0.00776	0.01323	0.44362	0.01112	0.03338	0.46911	0.00789	-0.00376
	hsp	0.32305	0.00990	-0.00515	0.33906	0.01112	0.01415	0.38390	0.01233	-0.02320
	mal	0.48442	0.00788	0.01240	0.55281	0.01168	0.03924	0.47594	0.00804	-0.00960
	mfg	0.02485	0.00061	0.00072	0.02277	0.00052	0.00100	0.04254	0.00103	0.00182
	nam	0.56762	0.01228	0.00048	0.55744	0.01440	0.02620	0.63889	0.01442	-0.02462
	nec	0.31383	0.00811	0.01312	0.37955	0.01144	0.02939	0.30294	0.00770	0.00211
	neg	0.21063	0.00339	0.00834	0.21773	0.00493	0.02021	0.21835	0.00364	-0.00309
	wag	0.75264	0.00996	0.03824	0.82978	0.01495	0.07673	0.75032	0.00927	0.00353
	wbg	0.48703	0.00559	0.02595	0.49201	0.01009	0.05131	0.51470	0.00431	0.00294
	whg	0.44417	0.00456	0.01847	0.43090	0.00789	0.04345	0.50203	0.00465	-0.01011
	wht	0.36062	0.00755	0.01287	0.43385	0.01149	0.03320	0.34173	0.00700	-0.00308
	wng	0.56089	0.00866	0.02899	0.54738	0.01338	0.05668	0.61198	0.00662	0.00185

Table 11d. County Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	**tau(grd)**	**cov(int,grd)**	**tau(int)**	**tau(grd)**	**cov(int,grd)**	**tau(int)**	**tau(grd)**	**cov(int,grd)**
CS Scale	all	0.05935	0.00099	0.00024	0.06826	0.00141	0.00105	0.05586	0.00089	-0.00025
	asn	0.10044	0.00156	0.00174	0.11564	0.00180	0.00314	0.09373	0.00155	0.00099
	blk	0.04451	0.00121	0.00062	0.04865	0.00158	0.00122	0.04518	0.00106	0.00029
	ecd	0.03655	0.00109	-0.00057	0.04376	0.00143	-0.00001	0.03476	0.00103	-0.00092
	fem	0.05456	0.00097	0.00049	0.06044	0.00137	0.00117	0.05489	0.00088	0.00019
	hsp	0.03631	0.00141	-0.00106	0.03891	0.00176	-0.00031	0.04034	0.00134	-0.00171
	mal	0.06526	0.00102	0.00007	0.07715	0.00141	0.00098	0.05867	0.00093	-0.00052
	mfg	0.00354	0.00008	0.00003	0.00359	0.00007	-0.00007	0.00502	0.00012	0.00024
	nam	0.07145	0.00143	-0.00138	0.07302	0.00173	-0.00059	0.07461	0.00138	-0.00220
	nec	0.04370	0.00102	0.00057	0.05417	0.00146	0.00109	0.03892	0.00090	0.00038
	neg	0.02469	0.00034	0.00040	0.02618	0.00038	0.00078	0.02423	0.00034	0.00004
	wag	0.07127	0.00091	0.00192	0.07878	0.00099	0.00252	0.06806	0.00094	0.00162
	wbg	0.05101	0.00053	0.00150	0.05305	0.00068	0.00228	0.05115	0.00047	0.00087
	whg	0.04700	0.00048	0.00092	0.04739	0.00054	0.00171	0.04975	0.00051	-0.00001
	wht	0.04520	0.00095	0.00027	0.05612	0.00140	0.00088	0.03936	0.00083	-0.00008
	wng	0.06782	0.00089	0.00126	0.06950	0.00106	0.00235	0.06825	0.00078	0.00036
GCS Scale	all	0.62526	0.01125	0.02047	0.69602	0.01782	0.05614	0.63067	0.01024	-0.00860
	asn	1.05245	0.01845	0.04681	1.17899	0.02567	0.10650	1.05937	0.01752	0.00119
	blk	0.46840	0.01296	0.02005	0.49523	0.01836	0.04512	0.51029	0.01204	-0.00179
	ecd	0.38322	0.01141	0.00550	0.44460	0.01562	0.02989	0.39244	0.01191	-0.01394
	fem	0.57509	0.01113	0.02153	0.61770	0.01725	0.05241	0.61942	0.01002	-0.00345
	hsp	0.38021	0.01451	-0.00025	0.39346	0.01808	0.02397	0.45553	0.01556	-0.02339
	mal	0.68550	0.01158	0.02081	0.78599	0.01806	0.06115	0.66272	0.01076	-0.01207
	mfg	0.03808	0.00085	0.00130	0.03617	0.00070	0.00172	0.05658	0.00133	0.00219
	nam	0.74660	0.01455	0.00464	0.73488	0.01844	0.04212	0.84568	0.01628	-0.03335
	nec	0.45911	0.01180	0.01953	0.55169	0.01774	0.04738	0.43988	0.01020	0.00027
	neg	0.26046	0.00387	0.01051	0.26572	0.00560	0.02459	0.27382	0.00390	-0.00215
	wag	0.74982	0.01123	0.04122	0.80330	0.01574	0.07541	0.76851	0.01027	0.01098
	wbg	0.53572	0.00675	0.02897	0.53991	0.01125	0.05668	0.57797	0.00514	0.00424
	whg	0.49607	0.00580	0.02267	0.48480	0.00919	0.04800	0.56201	0.00577	-0.00555
	wht	0.47350	0.01090	0.01683	0.57239	0.01702	0.04670	0.44513	0.00947	-0.00519
	wng	0.71138	0.01025	0.03230	0.70513	0.01539	0.06780	0.77264	0.00896	-0.00341

Table 11e. Geographic District Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)
CS Scale	all	0.11878	0.00180	0.00170	0.12954	0.00262	0.00299	0.11507	0.00155	0.00080
	asn	0.16023	0.00194	0.00341	0.18073	0.00248	0.00583	0.14962	0.00183	0.00182
	blk	0.07542	0.00186	0.00158	0.07803	0.00237	0.00225	0.07844	0.00162	0.00112
	ecd	0.05810	0.00187	-0.00022	0.06642	0.00253	0.00039	0.05632	0.00166	-0.00057
	fem	0.11090	0.00168	0.00170	0.11521	0.00244	0.00273	0.11435	0.00145	0.00102
	hsp	0.07585	0.00203	-0.00034	0.07569	0.00264	0.00081	0.08366	0.00187	-0.00143
	mal	0.12130	0.00185	0.00161	0.13741	0.00259	0.00318	0.11192	0.00163	0.00055
	mfg	0.00483	0.00013	0.00010	0.00486	0.00011	0.00001	0.00642	0.00017	0.00032
	nam	0.08941	0.00261	-0.00063	0.09234	0.00335	0.00039	0.09154	0.00213	-0.00151
	nec	0.08408	0.00178	0.00167	0.09819	0.00258	0.00242	0.07730	0.00153	0.00140
	neg	0.02899	0.00041	0.00016	0.03098	0.00043	0.00048	0.02809	0.00041	-0.00015
	wag	0.07164	0.00085	0.00141	0.08102	0.00092	0.00192	0.06692	0.00086	0.00119
	wbg	0.05384	0.00058	0.00116	0.05532	0.00067	0.00170	0.05454	0.00052	0.00069
	whg	0.04561	0.00055	0.00043	0.04552	0.00056	0.00103	0.04847	0.00060	-0.00034
	wht	0.08790	0.00170	0.00162	0.09992	0.00252	0.00239	0.08260	0.00143	0.00118
	wng	0.06559	0.00127	0.00107	0.06525	0.00132	0.00173	0.06736	0.00123	0.00040
GCS Scale	all	1.25242	0.02061	0.05144	1.31916	0.03397	0.11488	1.29997	0.01763	-0.00303
	asn	1.68608	0.02323	0.07975	1.84582	0.03808	0.17547	1.69068	0.02058	0.00430
	blk	0.79271	0.02041	0.03822	0.79428	0.02832	0.07447	0.88567	0.01834	0.00407
	ecd	0.60832	0.01986	0.01521	0.67430	0.02748	0.04937	0.63646	0.01913	-0.01247
	fem	1.17131	0.01940	0.04918	1.17414	0.03141	0.10328	1.29172	0.01644	-0.00043
	hsp	0.79649	0.02162	0.01789	0.76869	0.02940	0.05961	0.94537	0.02177	-0.02501
	mal	1.27535	0.02120	0.05191	1.39928	0.03418	0.12166	1.26455	0.01857	-0.00577
	mfg	0.05149	0.00144	0.00244	0.04908	0.00130	0.00336	0.07245	0.00185	0.00300
	nam	0.93624	0.02732	0.01881	0.93393	0.03608	0.06752	1.03722	0.02480	-0.02742
	nec	0.88758	0.02030	0.04294	1.00033	0.03168	0.08961	0.87353	0.01731	0.00762
	neg	0.30504	0.00459	0.00956	0.31490	0.00590	0.02486	0.31758	0.00476	-0.00480
	wag	0.75194	0.01034	0.03526	0.82442	0.01437	0.07063	0.75563	0.00951	0.00615
	wbg	0.56481	0.00699	0.02700	0.56267	0.01061	0.05246	0.61639	0.00580	0.00182
	whg	0.48093	0.00630	0.01741	0.46448	0.00852	0.04004	0.54817	0.00688	-0.00921
	wht	0.92772	0.01942	0.04336	1.01842	0.03116	0.09019	0.93365	0.01613	0.00445
	wng	0.68840	0.01406	0.03016	0.66093	0.01710	0.05931	0.76200	0.01412	-0.00248

Table 11f. Administrative District Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)	tau(int)	tau(grd)	cov(int,grd)
CS Scale	all	0.17120	0.00237	0.00087	0.18710	0.00333	0.00251	0.16368	0.00204	-0.00035
	asn	0.16953	0.00221	0.00271	0.19153	0.00279	0.00491	0.15792	0.00208	0.00132
	blk	0.10285	0.00256	0.00130	0.10927	0.00317	0.00233	0.10270	0.00231	0.00059
	ecd	0.08972	0.00243	-0.00068	0.10235	0.00320	0.00021	0.08466	0.00217	-0.00125
	fem	0.15462	0.00215	0.00115	0.16202	0.00304	0.00252	0.15613	0.00182	0.00017
	hsp	0.09277	0.00253	-0.00040	0.09521	0.00322	0.00089	0.09871	0.00234	-0.00165
	mal	0.16613	0.00242	0.00068	0.18785	0.00327	0.00255	0.15219	0.00212	-0.00062
	mfg	0.00524	0.00015	0.00014	0.00530	0.00013	0.00006	0.00677	0.00019	0.00035
	nam	0.10266	0.00289	-0.00114	0.10528	0.00365	-0.00006	0.10540	0.00238	-0.00206
	nec	0.12928	0.00225	0.00083	0.14929	0.00316	0.00144	0.11783	0.00191	0.00068
	neg	0.03450	0.00045	0.00027	0.03662	0.00047	0.00064	0.03345	0.00045	-0.00008
	wag	0.07224	0.00091	0.00125	0.08128	0.00096	0.00172	0.06778	0.00092	0.00107
	wbg	0.05536	0.00063	0.00121	0.05665	0.00073	0.00176	0.05621	0.00056	0.00074
	whg	0.04647	0.00058	0.00044	0.04644	0.00060	0.00109	0.04917	0.00063	-0.00035
	wht	0.11410	0.00201	0.00175	0.12879	0.00293	0.00247	0.10720	0.00165	0.00132
	wng	0.06388	0.00129	0.00082	0.06378	0.00134	0.00150	0.06534	0.00126	0.00018
GCS Scale	all	1.80469	0.02645	0.05829	1.90266	0.04256	0.14761	1.84964	0.02337	-0.02078
	asn	1.78196	0.02565	0.07568	1.95394	0.04043	0.17382	1.78416	0.02353	-0.00213
	blk	1.08004	0.02778	0.04371	1.11285	0.03731	0.09651	1.16073	0.02628	-0.00401
	ecd	0.93960	0.02570	0.02006	1.03956	0.03509	0.07157	0.95724	0.02503	-0.02262
	fem	1.63079	0.02427	0.05627	1.64976	0.03884	0.13216	1.76427	0.02088	-0.01421
	hsp	0.97505	0.02699	0.02317	0.96846	0.03603	0.07383	1.11565	0.02706	-0.02876
	mal	1.74563	0.02684	0.05589	1.90936	0.04195	0.14858	1.72010	0.02444	-0.02288
	mfg	0.05579	0.00166	0.00299	0.05373	0.00156	0.00413	0.07635	0.00205	0.00333
	nam	1.07456	0.03010	0.01652	1.06463	0.03869	0.07135	1.19440	0.02789	-0.03495
	nec	1.36268	0.02497	0.04874	1.51832	0.03817	0.11410	1.33258	0.02170	-0.00431
	neg	0.36315	0.00504	0.01244	0.37275	0.00667	0.03005	0.37803	0.00509	-0.00446
	wag	0.75839	0.01082	0.03388	0.82710	0.01448	0.06890	0.76525	0.01017	0.00475
	wbg	0.58084	0.00755	0.02795	0.57678	0.01126	0.05402	0.63550	0.00629	0.00226
	whg	0.49001	0.00667	0.01793	0.47411	0.00895	0.04124	0.55619	0.00728	-0.00943
	wht	1.20428	0.02275	0.05276	1.31352	0.03638	0.11046	1.21264	0.01863	0.00363
	wng	0.67002	0.01424	0.02730	0.64560	0.01693	0.05623	0.73927	0.01439	-0.00487

Table 11g. School Variances and Covariances

		Pooled			Math			RLA		
		tau(int)	**tau(grd)**	**cov(int,grd)**	**tau(int)**	**tau(grd)**	**cov(int,grd)**	**tau(int)**	**tau(grd)**	**cov(int,grd)**
CS Scale	all	0.21026	0.00371	0.00241	0.22497	0.00533	0.00525	0.20411	0.00285	0.00017
GCS Scale	all	3.34822	0.04037	0.09073	3.37881	0.06189	0.19985	3.44687	0.03220	-0.01267

Table 12a. State Reliabilities

		Pooled		Math		RLA	
		rel(int)	rel(grd)	rel(int)	rel(grd)	rel(int)	rel(grd)
CS Scale	all	0.999	0.968	0.999	0.945	0.999	0.962
	asn	0.999	0.927	0.998	0.900	0.998	0.892
	blk	0.997	0.939	0.995	0.901	0.995	0.915
	ecd	0.996	0.961	0.994	0.923	0.994	0.950
	fem	0.999	0.960	0.998	0.934	0.998	0.952
	hsp	0.997	0.960	0.994	0.921	0.995	0.951
	mal	0.999	0.963	0.998	0.934	0.998	0.955
	mfg	0.989	0.802	0.974	0.623	0.989	0.827
	nam	0.997	0.899	0.994	0.821	0.995	0.865
	nec	0.996	0.937	0.994	0.909	0.993	0.920
	neg	0.997	0.937	0.995	0.873	0.996	0.928
	wag	0.999	0.916	0.998	0.860	0.998	0.870
	wbg	0.999	0.896	0.997	0.847	0.997	0.840
	whg	0.999	0.936	0.998	0.875	0.998	0.923
	wht	0.999	0.967	0.998	0.949	0.999	0.954
	wng	0.998	0.808	0.995	0.722	0.996	0.720
GCS Scale	all	0.999	0.968	0.999	0.950	0.999	0.965
	asn	0.998	0.928	0.998	0.952	0.998	0.896
	blk	0.997	0.932	0.995	0.917	0.995	0.921
	ecd	0.996	0.955	0.994	0.906	0.995	0.955
	fem	0.999	0.959	0.998	0.937	0.998	0.957
	hsp	0.996	0.956	0.994	0.923	0.995	0.954
	mal	0.999	0.962	0.998	0.941	0.998	0.959
	mfg	0.990	0.800	0.974	0.603	0.989	0.825
	nam	0.997	0.879	0.994	0.829	0.996	0.880
	nec	0.995	0.929	0.994	0.906	0.993	0.926
	neg	0.995	0.889	0.995	0.891	0.996	0.931
	wag	0.999	0.936	0.998	0.941	0.998	0.866
	wbg	0.998	0.882	0.997	0.919	0.997	0.830
	whg	0.999	0.933	0.998	0.942	0.998	0.920
	wht	0.999	0.966	0.999	0.967	0.999	0.956
	wng	0.997	0.831	0.995	0.874	0.996	0.731

Table 12b. Commuting Zone Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.998	0.944	0.995	0.919	0.996	0.905
	asn	0.972	0.731	0.955	0.644	0.947	0.628
	blk	0.964	0.773	0.942	0.710	0.941	0.682
	ecd	0.996	0.931	0.991	0.891	0.992	0.888
	fem	0.997	0.928	0.993	0.899	0.994	0.882
	hsp	0.973	0.839	0.956	0.773	0.958	0.771
	mal	0.997	0.929	0.994	0.898	0.994	0.883
	mfg	0.953	0.644	0.912	0.453	0.941	0.629
	nam	0.953	0.658	0.913	0.565	0.927	0.545
	nec	0.994	0.924	0.988	0.891	0.988	0.872
	neg	0.991	0.843	0.982	0.776	0.982	0.782
	wag	0.969	0.657	0.950	0.546	0.941	0.559
	wbg	0.971	0.690	0.951	0.635	0.949	0.571
	whg	0.979	0.706	0.965	0.638	0.966	0.616
	wht	0.993	0.924	0.989	0.904	0.986	0.870
	wng	0.955	0.564	0.918	0.493	0.925	0.420
GCS Scale	all	0.998	0.945	0.995	0.930	0.996	0.911
	asn	0.971	0.735	0.955	0.696	0.948	0.632
	blk	0.964	0.774	0.942	0.737	0.941	0.685
	ecd	0.996	0.927	0.991	0.896	0.992	0.896
	fem	0.997	0.931	0.993	0.912	0.994	0.888
	hsp	0.973	0.833	0.955	0.770	0.958	0.778
	mal	0.997	0.931	0.994	0.911	0.994	0.890
	mfg	0.954	0.643	0.912	0.456	0.942	0.626
	nam	0.953	0.643	0.912	0.567	0.927	0.558
	nec	0.993	0.923	0.988	0.895	0.988	0.878
	neg	0.990	0.835	0.982	0.828	0.982	0.784
	wag	0.969	0.672	0.950	0.632	0.941	0.560
	wbg	0.970	0.705	0.950	0.707	0.950	0.572
	whg	0.979	0.718	0.965	0.730	0.966	0.623
	wht	0.993	0.927	0.989	0.916	0.986	0.875
	wng	0.955	0.577	0.918	0.572	0.925	0.426

Table 12c. Metropolitan Area Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.998	0.949	0.996	0.926	0.996	0.910
	asn	0.974	0.683	0.956	0.586	0.946	0.566
	blk	0.969	0.776	0.948	0.713	0.945	0.671
	ecd	0.995	0.939	0.992	0.906	0.991	0.900
	fem	0.997	0.939	0.995	0.914	0.995	0.896
	hsp	0.984	0.858	0.972	0.794	0.972	0.787
	mal	0.998	0.939	0.996	0.912	0.995	0.894
	mfg	0.962	0.634	0.925	0.445	0.952	0.595
	nam	0.916	0.591	0.868	0.496	0.870	0.476
	nec	0.995	0.927	0.992	0.898	0.989	0.870
	neg	0.993	0.859	0.987	0.788	0.985	0.785
	wag	0.966	0.595	0.943	0.485	0.931	0.482
	wbg	0.972	0.672	0.953	0.605	0.950	0.543
	whg	0.987	0.730	0.976	0.643	0.976	0.633
	wht	0.997	0.935	0.994	0.914	0.992	0.884
	wng	0.915	0.507	0.865	0.425	0.866	0.354
GCS Scale	all	0.998	0.951	0.996	0.938	0.996	0.916
	asn	0.974	0.694	0.956	0.650	0.946	0.568
	blk	0.969	0.777	0.948	0.738	0.945	0.674
	ecd	0.995	0.936	0.992	0.905	0.991	0.907
	fem	0.997	0.942	0.995	0.928	0.995	0.901
	hsp	0.983	0.852	0.971	0.792	0.972	0.795
	mal	0.998	0.942	0.996	0.927	0.995	0.901
	mfg	0.963	0.627	0.925	0.453	0.953	0.590
	nam	0.915	0.581	0.867	0.498	0.870	0.484
	nec	0.995	0.929	0.992	0.910	0.989	0.874
	neg	0.992	0.851	0.987	0.839	0.986	0.788
	wag	0.966	0.621	0.943	0.578	0.931	0.480
	wbg	0.972	0.687	0.952	0.686	0.950	0.540
	whg	0.987	0.746	0.976	0.745	0.976	0.639
	wht	0.996	0.938	0.994	0.927	0.992	0.889
	wng	0.914	0.522	0.865	0.488	0.866	0.356

Table 12d. County Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.997	0.925	0.993	0.893	0.993	0.862
	asn	0.927	0.580	0.887	0.476	0.884	0.471
	blk	0.932	0.699	0.894	0.624	0.895	0.585
	ecd	0.992	0.907	0.984	0.862	0.983	0.838
	fem	0.995	0.903	0.989	0.866	0.990	0.826
	hsp	0.946	0.756	0.909	0.680	0.919	0.645
	mal	0.996	0.904	0.991	0.862	0.990	0.830
	mfg	0.921	0.511	0.856	0.327	0.893	0.460
	nam	0.894	0.537	0.837	0.442	0.846	0.415
	nec	0.991	0.888	0.983	0.848	0.979	0.801
	neg	0.979	0.734	0.959	0.628	0.960	0.624
	wag	0.908	0.490	0.858	0.379	0.857	0.389
	wbg	0.935	0.574	0.895	0.488	0.898	0.450
	whg	0.951	0.577	0.915	0.473	0.924	0.469
	wht	0.992	0.900	0.986	0.867	0.983	0.822
	wng	0.888	0.451	0.830	0.356	0.835	0.317
GCS Scale	all	0.997	0.929	0.993	0.911	0.993	0.867
	asn	0.926	0.594	0.888	0.538	0.884	0.471
	blk	0.932	0.700	0.894	0.648	0.896	0.588
	ecd	0.992	0.906	0.984	0.870	0.984	0.846
	fem	0.995	0.908	0.989	0.887	0.990	0.831
	hsp	0.945	0.752	0.909	0.686	0.920	0.652
	mal	0.996	0.909	0.991	0.886	0.990	0.836
	mfg	0.923	0.510	0.855	0.341	0.893	0.455
	nam	0.893	0.528	0.836	0.455	0.847	0.423
	nec	0.990	0.893	0.983	0.868	0.980	0.805
	neg	0.978	0.736	0.959	0.697	0.960	0.626
	wag	0.908	0.514	0.858	0.457	0.857	0.384
	wbg	0.934	0.595	0.895	0.569	0.898	0.446
	whg	0.951	0.594	0.916	0.568	0.924	0.470
	wht	0.992	0.905	0.986	0.884	0.983	0.827
	wng	0.888	0.462	0.830	0.421	0.836	0.319

Table 12e. Geographic District Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.992	0.892	0.987	0.863	0.986	0.804
	asn	0.926	0.576	0.896	0.492	0.889	0.458
	blk	0.904	0.639	0.861	0.564	0.865	0.513
	ecd	0.979	0.851	0.967	0.806	0.962	0.747
	fem	0.989	0.856	0.983	0.822	0.982	0.748
	hsp	0.931	0.690	0.894	0.621	0.900	0.565
	mal	0.990	0.862	0.984	0.821	0.981	0.763
	mfg	0.842	0.400	0.759	0.251	0.788	0.323
	nam	0.845	0.528	0.785	0.448	0.787	0.376
	nec	0.981	0.843	0.972	0.807	0.965	0.735
	neg	0.939	0.563	0.908	0.442	0.896	0.436
	wag	0.877	0.428	0.832	0.319	0.820	0.326
	wbg	0.877	0.437	0.825	0.348	0.826	0.318
	whg	0.895	0.444	0.843	0.332	0.845	0.343
	wht	0.985	0.858	0.978	0.827	0.974	0.753
	wng	0.811	0.387	0.737	0.280	0.742	0.272
GCS Scale	all	0.992	0.898	0.987	0.887	0.986	0.810
	asn	0.925	0.592	0.897	0.567	0.890	0.458
	blk	0.904	0.643	0.861	0.593	0.865	0.515
	ecd	0.978	0.852	0.967	0.816	0.963	0.754
	fem	0.989	0.864	0.983	0.851	0.982	0.752
	hsp	0.931	0.691	0.894	0.640	0.901	0.571
	mal	0.989	0.869	0.984	0.853	0.981	0.768
	mfg	0.843	0.405	0.757	0.275	0.788	0.319
	nam	0.844	0.525	0.784	0.461	0.788	0.383
	nec	0.981	0.849	0.972	0.831	0.966	0.738
	neg	0.939	0.568	0.908	0.503	0.897	0.439
	wag	0.877	0.450	0.832	0.393	0.820	0.323
	wbg	0.876	0.456	0.825	0.421	0.826	0.316
	whg	0.895	0.456	0.843	0.403	0.846	0.346
	wht	0.985	0.865	0.978	0.850	0.974	0.756
	wng	0.810	0.394	0.736	0.322	0.742	0.274

Table 12f. Administrative District Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.969	0.843	0.958	0.810	0.956	0.756
	asn	0.899	0.549	0.865	0.466	0.858	0.436
	blk	0.882	0.633	0.842	0.558	0.841	0.519
	ecd	0.948	0.805	0.931	0.757	0.925	0.706
	fem	0.964	0.806	0.950	0.768	0.950	0.699
	hsp	0.903	0.668	0.865	0.598	0.869	0.550
	mal	0.962	0.812	0.951	0.767	0.946	0.716
	mfg	0.759	0.355	0.677	0.227	0.704	0.283
	nam	0.837	0.523	0.777	0.442	0.781	0.377
	nec	0.950	0.786	0.936	0.748	0.928	0.680
	neg	0.879	0.494	0.841	0.387	0.831	0.379
	wag	0.838	0.394	0.787	0.289	0.777	0.299
	wbg	0.824	0.394	0.768	0.312	0.770	0.285
	whg	0.847	0.403	0.791	0.300	0.794	0.310
	wht	0.953	0.800	0.941	0.769	0.935	0.695
	wng	0.785	0.370	0.711	0.266	0.714	0.260
GCS Scale	all	0.968	0.847	0.958	0.834	0.957	0.762
	asn	0.898	0.559	0.865	0.530	0.858	0.437
	blk	0.882	0.636	0.842	0.584	0.841	0.523
	ecd	0.948	0.805	0.931	0.768	0.926	0.713
	fem	0.964	0.812	0.951	0.797	0.951	0.704
	hsp	0.903	0.669	0.866	0.618	0.870	0.556
	mal	0.962	0.816	0.951	0.797	0.947	0.722
	mfg	0.760	0.361	0.676	0.252	0.705	0.279
	nam	0.836	0.519	0.776	0.452	0.782	0.384
	nec	0.950	0.789	0.936	0.770	0.928	0.684
	neg	0.879	0.501	0.841	0.447	0.831	0.381
	wag	0.837	0.412	0.788	0.353	0.777	0.296
	wbg	0.824	0.410	0.769	0.377	0.770	0.283
	whg	0.846	0.414	0.791	0.365	0.794	0.312
	wht	0.953	0.806	0.941	0.792	0.935	0.698
	wng	0.784	0.375	0.710	0.303	0.715	0.261

Table 12g. School Reliabilities

		Pooled		Math		RLA	
		rel(int)	**rel(grd)**	**rel(int)**	**rel(grd)**	**rel(int)**	**rel(grd)**
CS Scale	all	0.964	0.703	0.950	0.648	0.951	0.543
GCS Scale	all	0.972	0.712	0.960	0.676	0.961	0.552

Table 13. Suppressed Estimates by Unit Post-Estimation, Long Form Data for Districts, Counties, Metropolitan Areas, Commuting Zones, and States

	sedaadmin		sedacounty		sedacz		sedafips		sedalea		sedametro	
NCES privacy restrictions	6,706,768	38.89%	1,083,775	23.89%	180,581	17.04%	397	0.43%	5,497,707	36.52%	302,095	19.11%
Standard error 1 or higher	92	0.00%	4	0.00%	3	0.00%		0.00%	63	0.00%		0.00%
Alternative assessments > 20%	2,712	0.02%		0.00%		0.00%		0.00%	419	0.00%		0.00%
Missing or suppressed mean for All subgroup	267	0.00%	5	0.00%	5	0.00%		0.00%	11	0.00%		0.00%
Not suppressed	10,535,101	61.09%	3,451,987	76.11%	879,141	82.96%	92,436	99.57%	9,556,726	63.48%	1,278,352	80.89%
Total	17,244,940	100.00%	4,535,771	100.00%	1,059,730	100.00%	92,833	100.00%	15,054,926	100.00%	1,580,447	100.00%

Note: sedafips = State; sedacz = Commuting zone; sedametro = Metro; sedacounty = County; sedalea = Geographic district; sedaadmin = Administrative District

Table 14. Suppressed Estimates by Unit Post-Estimation, Pooled Data for Schools, Districts, Counties, Metropolitan areas, Commuting zones, and States

	sedaadmin		sedacounty		sedacz		sedafips		sedalea		sedametro		sedasch	
NCES privacy restrictions	28,755	13.33%	3,550	7.73%	226	2.31%		0.00%	19,977	11.99%	353	2.38%	1,766	2.14%
Low reliability	7,555	3.50%	289	0.63%	26	0.27%		0.00%	1,147	0.69%	53	0.36%	4,148	5.02%
Alternative assessments > 20%	291	0.13%	12	0.03%	2	0.02%		0.00%	42	0.03%	2	0.01%	106	0.13%
Missing or suppressed mean for All subgroup	1,306	0.61%		0.00%		0.00%		0.00%	69	0.04%		0.00%	3,212	3.88%
Other	178	0.08%	24	0.05%	4	0.04%		0.00%	107	0.06%	16	0.11%		0.00%
Not suppressed	177,581	82.34%	42,062	91.56%	9,524	97.36%	816	100.00%	145,337	87.20%	14,418	97.14%	73,471	88.84%
Total	215,666	100.00%	45,937	100.00%	9,782	100.00%	816	100.00%	166,679	100.00%	14,842	100.00%	82,703	100.00%

Note: sedafips = State; sedacz = Commuting zone; sedametro = Metro; sedacounty = County; sedalea = Geographic district; sedaadmin = Administrative District; sedasch = School

Table 15. Component Loadings and Summary Statistics for Socioeconomic Status Composite Constructin.

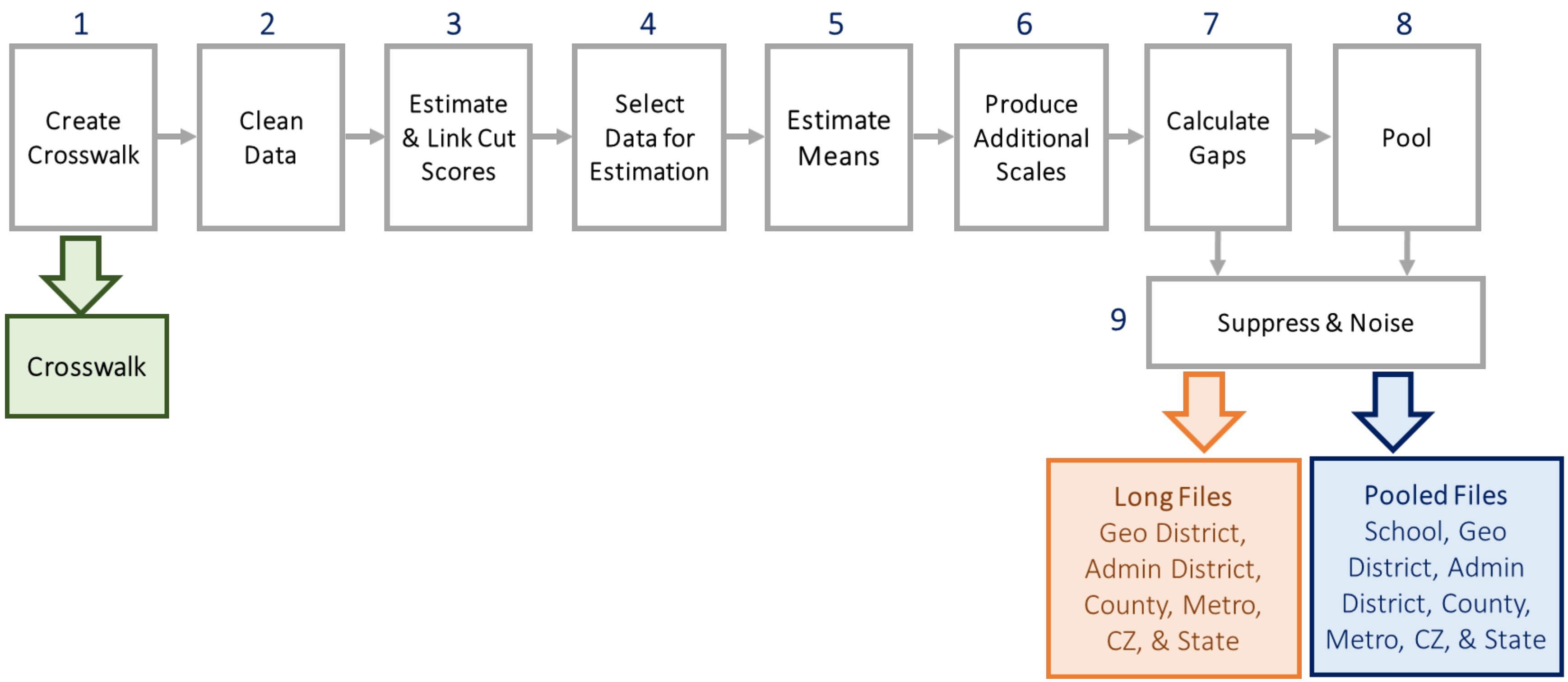
	Standardized Loadings	Unstandardized Loadings	Mean	SD
log(Median Family Income)	0.914	0.638	10.886	0.335
% with BA or Higher	0.674	1.170	0.285	0.135
Poverty Rate	-0.925	-2.664	0.151	0.081
SNAP Eligibility Rate	-0.931	-2.958	0.115	0.074
Unemployment Rate	-0.791	-5.221	0.097	0.035
Single Mother Headed Household Rate	-0.799	-2.315	0.199	0.081

Table 16. Summary Statistics at Different Values of the Socioeconomic Status Composite.

	SES Composite						
	below -2.5	-2.5 to -1.5	-1.5 to -.5	-.5 to .5	.5 to 1.5	1.5 to 2.5	above 2.5
log(Median Family Income)	10.17	10.31	10.51	10.74	11.03	11.55	12.11
% with BA or Higher	0.10	0.12	0.14	0.18	0.27	0.54	0.79
Poverty Rate	0.35	0.29	0.21	0.14	0.08	0.04	0.03
SNAP Eligibility Rate	0.32	0.26	0.18	0.11	0.06	0.02	0.01
Unemployment Rate	0.14	0.10	0.08	0.06	0.05	0.04	0.04
Single Mother Headed Household Rate	0.39	0.30	0.22	0.16	0.12	0.10	0.07

Figures

Figure 1. SEDA 5.0 Construction Process



Appendices

Appendix A: Additional Detail on Statistical Methods

1. Estimating Means and Standard Deviations for Units that Cross State Lines

This section briefly describes how means, standard deviations, and standard errors are estimated for units serving BIE schools or units that cross state lines. As described above, we first estimate unit "component" means and standard deviations. We then estimate the overall unit mean as weighted averages of the component means and the unit standard deviations as estimates of total variance within a unit based on the component means and standard deviations.

Let $\hat{\mu}_d$ and $\hat{\sigma}_d$ be the estimated means and standard deviations for the D components $d = 1, \ldots,$ that will be aggregated for a given unit. We also have estimates of the standard errors for each mean and standard deviation, $se(\hat{\mu}_d)$ and $se(\hat{\sigma}_d)$. We do not include grade, subject, year, or state subscripts here for clarity.

To estimate the aggregate parameters, we make the simplifying assumption that $cov\left(\hat{\mu}_i, \hat{\mu}_j\right) = cov\left(\hat{\sigma}_i, \hat{\sigma}_j\right) = cov(\hat{\mu}_i, \hat{\sigma}_i) = 0$ for $i \neq j$. The derivations for these expressions are based on the formulas in the appendix of Reardon et al. (2017) used to estimate to overall mean and variance of a set of groups in the HETOP model. Let

$$p_d = \frac{n_d}{\sum_{d=1}^{D} n_d} = \frac{n_d}{N_c}$$

be the proportion of all students in the aggregate unit c that are in component d. We estimate the aggregate mean for aggregate unit c as the weighted average of the component estimated means,

$$\hat{\mu}_c = \sum_{d=1}^{D} p_d \hat{\mu}_d,$$

with an estimated standard error of

$$se(\hat{\mu}_c) = \sqrt{\sum_{d=1}^{D} [p_d^2 \cdot se(\hat{\mu}_d)^2]}.$$

We estimate the standard deviation for aggregate unit c as the square root of the sum of the estimated between and within-unit variance,

$$\hat{\sigma}_c = \sqrt{\sum_{d=1}^{D} [p_d(\hat{\mu}_d - \hat{\mu}_c)^2 + q_d \hat{\sigma}_d^2]},$$

with the associated estimated standard error

$$se(\hat{\sigma}_c) = \sqrt{z_c * \left(\frac{1}{\hat{\sigma}_c}\right)}.$$

In these expressions we define

$$q_d = \left(\frac{p_d + (n_d - 1)}{n_d}\right)\left(\frac{p_d}{1 + 2\left(\frac{1}{2\tilde{n}_c}\right)}\right),$$

$$\tilde{n}_c = \left[\left(\frac{1}{D}\right)\sum_{d=1}^{D}\left(\frac{1}{n_d - 1}\right)\right]^{-1},$$

and

$$z_c = \sum_{d=1}^{D} [(p_d^2(\hat{\mu}_d - \hat{\mu}_c)^2 se(\hat{\mu}_d)^2) + (q_d^2 \cdot \hat{\sigma}_d^2 \cdot se(\hat{\sigma}_d)^2)].$$

2. Constructing OLS Standard Errors from Pooled Models

In the SEDA 5.0 data, we release the OLS and EB estimates of the intercept and grade slope, as well as their standard errors, from the pooled models described in Section 9. The recovery of the OLS SEs is not straightforward from HLM. To recover these, we perform the estimation in two steps and calculate the OLS SEs post-estimation.

The remainder of this section describes the method and computational implementation. The equations are written to correspond to the pooling model shown in Equation 8.2; however, this procedure is the same for the other variant of our pooling models.

Step 1. We estimate σ^2 using the three-level model described in Equation 8.2 and define:

$$\hat{\phi}^2_{urygb} = \hat{\sigma}^2 + \omega^2_{urygb} \tag{A-2.1}$$

Where ω^2_{urygb} is the variance of the $\hat{y}^x_{urygb}$ estimate (either μ or σ). We assume that $\hat{\sigma}^2$ is a very precise estimate because of the large amount of data in the model.

Step 2. We then reweight the data and estimate a two-level HLM model:

Level-1:

$$\hat{\phi}^{-1}_{urygb}\hat{y}^x_{urygb} = [\beta_{0u} \quad \beta_{1u} \quad \beta_{2u} \quad \beta_{3u}] \begin{bmatrix} \hat{\phi}^{-1}_{drygb} \\ \hat{\phi}^{-1}_{urygb}(cohort_{urygb} - 2008) \\ \hat{\phi}^{-1}_{urygb}(grade_{urygb} - 5.5) \\ \hat{\phi}^{-1}_{urygb}(math_{urygb} - .5) \end{bmatrix} + \hat{\phi}^{-1}_{urygb} e_{urygb} \tag{A-2.2}$$

Level-2:

$$\begin{aligned} \beta_{0u} &= \gamma_{00} + \nu_{0u} \\ \beta_{0u} &= \gamma_{10} + \nu_{1u} \\ \beta_{0u} &= \gamma_{20} + \nu_{2u} \\ \beta_{0u} &= \gamma_{30} + \nu_{3u} \end{aligned}$$

After estimation, the HLM residual file contains the OLS and EB estimates, as well as the posterior variance matrices, $\boldsymbol{V}^{EB}_u$, for each unit. From the model, we also recover an estimate of $\boldsymbol{\tau}^2$. Using $\boldsymbol{V}^{EB}_u$ and $\hat{\boldsymbol{\tau}}^2$, we can calculate the standard errors of the OLS estimates for each unit as the inverse of:

$$(\boldsymbol{V}^{OLS}_u)^{-1} = (\boldsymbol{V}^{EB}_u)^{-1} - \hat{\boldsymbol{\tau}}^{-2}. \tag{A-2.3}$$

Appendix B: Covariates

1. List of Raw ACS Tables Used for SES Composite

Table Description	Table ID	Universe	Description	Usage	Derived Construct
Median household income	B19013	Households	median family income in the past 12 months	we adjust the reported median income for inflation (2012 constant dollars)	Median Income
Median household income	B19013B	Families with a householder who is Black or African American alone	median family income in the past 12 months	we adjust the reported median income for inflation (2012 constant dollars)	White Median Income
Median household income	B19013H	Families with a householder who is white alone (not Hispanic or Latino)	median family income in the past 12 months	we adjust the reported median income for inflation (2012 constant dollars)	Hispanic Median Income
Median household income	B19013I	Families with a householder who is Hispanic or Latino	median family income in the past 12 months	we adjust the reported median income for inflation (2012 constant dollars)	Black Median Income
Sex by Educational Attainment for the Population 25 and Older	B15002	Population 25 years and over	counts of number of individuals that fall into each of 16 educational attainment categories, by sex	we use the counts of men and women with a bachelor's degree or higher along with the total count to generate the BA+ rate	Bachelor's Degree Rate
Sex by Educational Attainment for the Population 25 and Older	C15002B	Black or African American alone population 25 years and over	counts of number of individuals that fall into each of 4 educational attainment categories, by sex	we use the counts of men and women with a bachelor's degree or higher along with the total count to generate the BA+ rate	Black Bachelor's Degree Rate
Sex by Educational Attainment for the Population 25 and Older	C15002H	White alone, not Hispanic or Latino population 25 years and over	counts of number of individuals that fall into each of 4 educational attainment categories, by sex	we use the counts of men and women with a bachelor's degree or higher along with the total count to generate the BA+ rate	White Bachelor's Degree Rate
Sex by Educational Attainment for the Population 25 and Older	C15002I	Hispanic or Latino population 25 years and over	counts of number of individuals that fall into each of 4 educational attainment categories, by sex	we use the counts of men and women with a bachelor's degree or higher along with the total count to generate the BA+ rate	Hispanic Bachelor's Degree Rate

Poverty Status in the Last 12 Months by Age	B17020	Population for whom poverty status is determined	counts of number of individuals living in households above and below the poverty line in various age bins	we use the counts of those living in poverty that are school aged (6-17 years old)	Poverty Rate, 6-17 Year Olds
Poverty Status in the Last 12 Months by Age	B17020B	Black or African American alone population for whom poverty status is determined	counts of number of individuals living in households above and below the poverty line in various age bins	we use the counts of those living in poverty that are school aged (6-17 years old)	Black Poverty Rate, 6-17 Year Olds
Poverty Status in the Last 12 Months by Age	B17020H	White alone, not Hispanic or Latino population for whom poverty status is determined	counts of number of individuals living in households above and below the poverty line in various age bins	we use the counts of those living in poverty that are school aged (6-17 years old)	White Poverty Rate, 6-17 Year Olds
Poverty Status in the Last 12 Months by Age	B17020I	Hispanic or Latino population for whom poverty status is determined	counts of number of individuals living in households above and below the poverty line in various age bins	we use the counts of those living in poverty that are school aged (6-17 years old)	Hispanic Poverty Rate, 6-17 Year Olds
Sex by Age by Employment Status for the Population 16 and Over	B23001	Population 25 to 64 years	counts of individuals by age, labor market status and employment status	we use the count of those employed divided by the count of those in the labor market for civilians ages 16-64 to compute an unemployment rate	Unemployment Rate
Sex by Age by Employment Status for the Population 16 and Over	C23002B	Black or African American alone, not Hispanic or Latino population 16 years and over	counts of individuals by age, labor market status and employment status	we use the count of those employed divided by the count of those in the labor market for civilians ages 16-64 to compute an unemployment rate	Black Unemployment Rate
Sex by Age by Employment Status for the Population 16 and Over	C23002H	White alone, not Hispanic or Latino population 16 years and over	counts of individuals by age, labor market status and employment status	we use the count of those employed divided by the count of those in the labor market for civilians ages 16-64 to compute an unemployment rate	White Unemployment Rate
Sex by Age by Employment Status for the Population 16 and Over	C23002I	Hispanic or Latino population 16 years and over	counts of individuals by age, labor market status and employment status	we use the count of those employed divided by the count of those in the labor market for civilians ages 16-64 to compute an unemployment rate	Hispanic Unemployment Rate

Receipt of Food Stamps/SNAP in the past 12 months by poverty status in the past 12 months for households	B22003	Households	counts of households receiving food stamps/SNAP benefits by poverty status	we use the counts of households receiving SNAP divided by the total number of households to compute the SNAP rate	SNAP Rate
Receipt of Food Stamps/SNAP in the past 12 months by poverty status in the past 12 months for households	B22005B	Households with a householder who is Black or African American alone	counts of households receiving food stamps/SNAP benefits by poverty status	we use the counts of households receiving SNAP divided by the total number of households to compute the SNAP rate	Black SNAP Rate
Receipt of Food Stamps/SNAP in the past 12 months by poverty status in the past 12 months for households	B22005H	Households with a householder who is White alone, not Hispanic or Latino	counts of households receiving food stamps/SNAP benefits by poverty status	we use the counts of households receiving SNAP divided by the total number of households to compute the SNAP rate	White SNAP Rate
Receipt of Food Stamps/SNAP in the past 12 months by poverty status in the past 12 months for households	B22005I	Households with a householder who is Hispanic or Latino	counts of households receiving food stamps/SNAP benefits by poverty status	we use the counts of households receiving SNAP divided by the total number of households to compute the SNAP rate	Hispanic SNAP Rate
Household Type	B11001	Households	counts of different types of households	we use the count of family households with a female householder, no husband present divided by the total number of family households	Female Headed Household Rate
Household Type	B11001B	Households with a householder who is Black or African American alone, not Hispanic or Latino	counts of different types of households	we use the count of family households with a female householder, no husband present divided by the total number of family households	Black Female Headed Household Rate
Household Type	B11001H	Households with a householder who is White alone, not Hispanic or Latino	counts of different types of households	we use the count of family households with a female householder, no husband present divided by the total number of family households	White Female Headed Household Rate
Household Type	B11001I	Households with a householder who is Hispanic or Latino	counts of different types of households	we use the count of family households with a female householder, no husband present divided by the total number of family households	Hispanic Female Headed Household Rate

2. Measurement Error, Attenuation Bias and Solutions

Formally, attenuation bias can be specified as follows. As an example, consider the true relationship between race-specific achievement and socioeconomic status we would like to estimate:

$$Y_g = \beta_{0g} + \beta_{1g}(SES_g) + \varepsilon_g \tag{B-2.1}$$

Where *Y* is White or non-White minority achievement in a unit (district, county, or metropolitan area) (g indexes group), and *SES* is the average socioeconomic status of the group. Race specific SES is measured with error and measurement error will be larger in units with relatively smaller sample sizes of non-White minorities. Thus, the data we observe are $W_g = SES_g + \varepsilon_g$. In this case, the bias in $\beta_{1g}$is known as attenuation bias. This bias can by quantified by multiplying by the variable's reliability $\lambda = \frac{var(SES_g)}{var(SES_g)+\sigma_1^2}$, i.e., the true variance of the variable SES_g relative to the true variance plus the variance of the measurement error.

To address attenuation bias, we use regression calibration, which makes use of the fact that the measurement error in SES_g (and consequently $SESGap$) are known from Census data.[23] Regression calibration is a method that replaces the error-prone variable W with its best linear prediction (blp). The best linear predictor of $SESGap$ can be defined as:

$$SESp_g^{blp} = E(SES_g) + \frac{cov(SES_g, W_g)}{var(W_g)}\left(W_g - E(W_g)\right)$$

$$= \mu + \frac{cov(SES_g, SES_g + \varepsilon_g)}{\sigma_{SES_g}^2 + \sigma_g^2}(W_g - \mu)$$

[23] Specifically, the ACS reports margins of error which can be easily converted standard errors for each Census variable. Appendix B3: Computing the sampling variance of sums of ACS variables provides a full description of how standard errors for cross-tabulated Census data are constructed.

$$= \mu + \lambda(W_g - \mu) \tag{B-2.2}$$

Note that SES_g^{blp} is "shrunken" towards the mean value of SES_g as a function of λ which, recall, is equal to the reliability of the variable SES_g and can be estimated as a random effect (or empirical Bayes estimate) from a generalized linear model.

Now, we show that regressing Y_g on SES_g^{blp} results in consistent estimates of β_{1g}.

$$\begin{aligned}
\frac{cov\left(Y_g, \mu + \lambda(W_g - \mu)\right)}{var\left(\mu + \lambda(W_g - \mu)\right)} &= \frac{cov(Y_g, \lambda W_g)}{\lambda^2\left(\sigma_{SES_g}^2 + \sigma_g^2\right)} \\
&= \frac{cov(Y_g, SES_g)}{\lambda\left(\sigma_{SES_g}^2 + \sigma_g^2\right)} \\
&= \frac{cov(Y_g, SES_g)}{\sigma_{SES_g}^2} = \beta_{1g}
\end{aligned} \tag{B-2.3}$$

3. Computing the Sampling Variance of Sums of ACS Variables

In each unit we are given counts in K cells: $\widehat{n1}_d, \widehat{n2}_d, \ldots, \widehat{nK}_d$; we also know total counts t_d; we also have margins of error of the counts

$$MoE(\widehat{n1}_d), MoE(\widehat{n2}_d), \ldots, MoE(\widehat{nK}_d).$$

We then compute the sampling variances of the

$$var(\widehat{nk}_d) = \left[\frac{MOE(\widehat{nk}_d)}{1.645}\right]^2$$

from these we compute

$$\widehat{pk}_d = \frac{\widehat{nk}_d}{t_d}$$

and

$$var(\widehat{pk}_d) = \frac{var(\widehat{nk}_d)}{t_d^2}.$$

We do not know the sampling rate in unit d; let's call it r_d. If the estimates come from a simple random sample, we would have

$$var(\widehat{pk}_d)^* = \frac{pk_d(1 - pk_d)}{r_d t_d}$$

The estimated design effect in district d for variable k is then

$$\widehat{Dk}_d = \frac{var(\widehat{pk}_d)}{var(\widehat{pk}_d)^*}$$

We can compute the average design effect in unit d as

$$D_d = \frac{1}{K} \sum_{k=1}^{K} \widehat{Dk}_d$$

Now we compute

$$\hat{P}_d = \frac{1}{t_d}\sum_{k=1}^{K}\widehat{nk}_d = \sum_{k=1}^{K}\widehat{pk}_d$$

We want to know $var\left(\hat{P}_d\right)$. If we had a simple random sample, we would have

$$var\left(\hat{P}_d\right)^* = \frac{P_d(1-P_d)}{r_d t_d}$$

Given the design effect in unit d, however, we would expect this to be inflated by a factor D_d. So, we have:

$$\begin{aligned}
var\left(\hat{P}_d\right) &= D_d var\left(\hat{P}_d\right)^* \\
&= D_d \frac{P_d(1-P_d)}{r_d t_d} \\
&= \left[\frac{1}{K}\sum_{k=1}^{K}\widehat{Dk}_d\right]\frac{P_d(1-P_d)}{r_d t_d} \\
&= \left[\frac{1}{K}\sum_{k=1}^{K}\frac{var\left(\widehat{pk}_d\right)}{var\left(\widehat{pk}_d\right)^*}\right]\frac{P_d(1-P_d)}{r_d t_d} \\
&= \left[\frac{1}{K}\sum_{k=1}^{K}\frac{r_d t_d var\left(\widehat{pk}_d\right)}{pk_d(1-pk_d)}\right]\frac{P_d(1-P_d)}{r_d t_d} \\
&= \left[\frac{1}{K}\sum_{k=1}^{K}\frac{var\left(\widehat{pk}_d\right)}{pk_d(1-pk_d)}\right]P_d(1-P_d) \\
&= \left[\frac{1}{K}\sum_{k=1}^{K}\frac{1}{nk_d}\right]P_d(1-P_d) \\
&= \frac{1}{\tilde{n}_d}P_d(1-P_d)
\end{aligned}$$

where nk_d=$\frac{pk_d(1-pk_d)}{var\left(\widehat{pk}_d\right)}$ is the effective sample size in cell k in unit d (the sample size nk_d such that $\frac{pk_d(1-pk_d)}{nk_d} = var\left(\widehat{pk}_d\right)$), and $\tilde{n}_d = \left(\frac{1}{K}\sum_{k=1}^{K}\frac{1}{nk_d}\right)^{-1}$ is the harmonic mean of the effective sample sizes across cells within unit d. Note that $\frac{\tilde{n}_d}{t_d} = \tilde{r}_d$ is the harmonic mean of the effective sampling rate across cells within d.

An alternate approach is to assume a common design effect across units

$$var(\hat{P}_d) = D_d var(\hat{P}_d)^*$$

$$= D_d \frac{P_d(1 - P_d)}{r_d t_d}$$

$$= D \frac{P_d(1 - P_d)}{r_d t_d}$$

where $D = \frac{1}{T}\sum_{j=1}^{J} t_j D_j$ is the average design effect across units (weighted by unit size to increase precision). We can write

$$D = \frac{1}{T}\sum_{j=1}^{J} t_j D_j$$

$$= \frac{1}{T}\sum_{j=1}^{J} t_j \left[\frac{1}{K}\sum_{k=1}^{K} \frac{r_j t_j}{nk_j}\right]$$

$$= \sum_{j=1}^{J} \frac{t_j}{T}\frac{r_j}{\tilde{r}_j}$$

So then,

$$var(\hat{P}_d) = D_d var(\hat{P}_d)^*$$

$$= D_d \frac{P_d(1 - P_d)}{r_d t_d}$$

$$= D \frac{P_d(1 - P_d)}{r_d t_d}$$

$$= \left[\sum_{j=1}^{J} \frac{t_j}{T} \frac{r_j}{\tilde{r}_j}\right] \frac{P_d(1-P_d)}{r_d t_d}$$

$$= \left[\sum_{j=1}^{J} \frac{t_j}{T} \frac{r_j t_d}{\tilde{r}_j t_d}\right] \frac{P_d(1-P_d)}{r_d t_d}$$

Assume r_j is constant across units and assume the effective sampling rate in unit j is independent of the unit size t_j; then this simplifies to

$$var\left(\hat{P}_d\right) = \frac{P_d(1-P_d)}{t_d \tilde{r}},$$

where

$$\tilde{r} = \left[\sum_{j=1}^{J} \frac{t_j}{T} \frac{1}{\tilde{r}_j}\right]^{-1}$$

is the (weighted) harmonic mean of the effective sampling rates. We can compute $\tilde{r}$ without knowing the actual sampling rates:

$$\tilde{r} = \left[\sum_{j=1}^{J} \frac{t_j}{T} \frac{1}{\frac{1}{t_j}\left(\frac{1}{K}\sum_{k=1}^{K} \frac{var\left(\widehat{pk}_j\right)}{pk_d\left(1-pk_j\right)}\right)^{-1}}\right]^{-1}$$

$$= \left[\sum_{j=1}^{J} \frac{t_j^2}{T} \left(\frac{1}{K}\sum_{k=1}^{K} \frac{var\left(\widehat{pk}_j\right)}{pk_d\left(1-pk_j\right)}\right)\right]^{-1}$$

To recap, we have two approaches to compute the sampling variance of $\hat{P}_d$:

1. For each unit, compute the harmonic mean of the effective sample size

$$\tilde{n}_d = \left(\frac{1}{K}\sum_{k=1}^{K} \frac{var\left(\widehat{pk}_d\right)}{pk_d(1-pk_d)}\right)^{-1}$$

then

$$Var(\hat{P}_d) = \frac{P_d(1-P_d)}{\tilde{n}_d}.$$

Or:

2. Compute the weighted harmonic mean of the effective sampling rate across units (using any of these formulas, all identical):

$$\tilde{r} = \left[\sum_{j=1}^{J} \frac{t_j}{T}\frac{1}{\tilde{r}_j}\right]^{-1}$$

$$= \left[\sum_{d=1}^{D} \frac{t_d^2}{T}\left(\frac{1}{K}\sum_{k=1}^{K} \frac{var(\widehat{pk}_d)}{pk_d(1-pk_d)}\right)\right]^{-1}$$

$$= \left[\frac{1}{(1.645^2)TK}\sum_{d=1}^{J}\sum_{k=1}^{K} \frac{MoE(\widehat{nk}_d)^2}{pk_d(1-pk_d)}\right]^{-1}$$

then

$$Var(\hat{P}_d) = \frac{P_d(1-P_d)}{\tilde{r}t_d}.$$

The first approach allows a different design effect in each unit, but the design effect is probably noisily estimated, so will have more noise in the estimated sampling variances. The second assumes a common design effect across units. Our decision criteria for generating sampling variances is as follows:

1. When $K = 1$ and $P_d > 0$, use the sampling variance provided by ACS, i.e., $var(\hat{p}_d) = \frac{var(\hat{n}_d)}{t_d^2}$

2. When $K = 1$ and $P_d = 0$, use the sampling variance method 2, i.e., $Var(\hat{P}_d) = \frac{P_d(1-P_d)}{\tilde{r}t_d}$, where $P_d = \frac{1}{t_d}$.
3. When $K > 1$ and $P_d > 0$, use the sampling variance method 2, i.e., $Var(\hat{P}_d) = \frac{P_d(1-P_d)}{\tilde{r}t_d}$
4. When $K > 1$ and $P_d = 0$, use the sampling variance method 2, i.e., $Var(\hat{P}_d) = \frac{P_d(1-P_d)}{\tilde{r}t_d}$, where $P_d = \frac{1}{t_d}$.

4. Estimating Sampling Variance of Composite SES Measures

Let $\hat{\hat{\mathbf{X}}}_d$ be the vector of 6 variables we use to construct the SES composite in unit d. Let $\mathbf{W}_d$ be the diagonal matrix containing the standard errors of $\hat{\mathbf{X}}_d$.[24]

Our estimated SES composite (S) in unit d is

$$\hat{S}_d = \hat{\hat{\mathbf{X}}}_d \mathbf{B},$$

where $\mathbf{B}$ is a 6×1 vector of unstandardized coefficients. The sampling variance of $\hat{S}_d$ is

$$var(\hat{S}_d) = \mathbf{B}' \mathbf{V}_d \mathbf{B},$$

where $\mathbf{V}_d$ is the covariance matrix of $\hat{\mathbf{X}}_d$. We know the diagonal elements of $\mathbf{V}_d$ ($\mathbf{W}_d$); but not the off-diagonals. We need to know $\mathbf{V}_d$ to get the standard error of $\hat{S}_d$. How can we compute $\mathbf{V}_d$?

Define $\mathbf{R}_d$**,** the correlation matrix describing the correlations of the estimates $\hat{\mathbf{X}}_d$. If we knew $\mathbf{R}_d$, then we can get

$$\mathbf{V}_d = \mathbf{W}_d \mathbf{R}_d \mathbf{W}_d.$$

The key is getting an estimate of $\mathbf{R}_d$. We can use PUMS data to estimate $\mathbf{R}$ empirically (via bootstrapped samples). We do this as follows:

a. Set $N = 5{,}000$, and $J = 1{,}000$ (or some other values)

b. Pick PUMA k.

c. From all families in PUMA k, draw a random sample of N families.

---

[24] Note that we get the standard errors of these variables from ACS. The exception is ln(median income), as we get a standard error for median income. Let $\widehat{M}_d$ be the estimated median income in unit d. The Delta method gives us

$$se[\ln(\widehat{M}_d)] \approx \frac{1}{\widehat{M}_d} se(\widehat{M}_d).$$

d. Compute $\widehat{\mathbf{X}}_k$ from the micro-data (so if $\mathbf{X}$ includes ln(median income), then estimate ln(median income) in PUMA k from the sample, and likewise for the 6 variables we include in $\mathbf{X}$).

e. Repeat (c) and (d) J times for PUMA k.

f. Estimate $\widehat{\mathbf{R}}_k^B$ from the J samples

g. Repeat (b)-(f) for all PUMAs $k = 1, \dots, K$.

h. Repeat (b)-(g) for each race/ethnic group r to get $\widehat{\mathbf{R}}_{kr}^B$. We might need to set $N = 1{,}000$ for race-ethnic groups, because race samples are smaller in each PUMA.

Next we examine how $\widehat{\mathbf{R}}_k$ and $\widehat{\mathbf{R}}_{kr}$ vary across PUMAs and race/ethnic groups. If $\widehat{\mathbf{R}}_k$ and $\widehat{\mathbf{R}}_{kr}$ are relatively constant across PUMAs and subgroups, we can just use a single common value of $\widehat{\mathbf{R}}$ for all units and subgroups. We find that they are generally similar, so we use a common $\widehat{\mathbf{R}}$ in all PUMAs.