# Educational opportunity in U.S. schools: Using population data to describe learning across space and time

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## Background and Purpose

There is a growing body of work characterizing the variation in educational opportunity across the U.S. among school districts, counties, and metropolitan areas (e.g., Reardon, 2019; Fahle & Reardon, 2018; Jang & Reardon, 2019). However, research to date has been unable to fully explore educational opportunity among U.S. schools. Nationally comparable school-level data was unavailable until recently with the release of the Stanford Education Data Archive V3.0 (Reardon et al., 2019).

This paper explores the variation in educational opportunities among students in U.S. public elementary and middle schools from 2009 to 2016. We also explore the associations between educational opportunities and school demographic (e.g., free and reduced-price lunch eligibility rates, race/ethnicity, etc.) and structural (e.g., grade level, charter status, etc.) characteristics. We use two test score-based measures to characterize educational opportunity in each school: average test scores and learning rates. Average test scores represent overall educational opportunities of students enrolled in a school. Learning rates, computed as the average per grade increase in scores at each school, reflect opportunities to learn during the years students are enrolled in a school. Our primary goals are to map these two dimensions of educational opportunity and to understand factors associated with higher educational opportunity in U.S. schools.

## Data and Analysis

SEDA draws on state proficiency data, housed in the ED*Facts* data collection system (U.S. Department of Education, 2018), to estimate the average performance and learning rate in nearly every school in the U.S. on a common scale. More detail on the data and methods used to create the data can be found in Fahle et al. (2019), Reardon, Kalogrides, and Ho (2019), Reardon, Shear, Castellano, and Ho (2017), and Shear and Reardon (2019).

We use the publicly-released average performance and learning rate estimates on the grade-cohort standardized scale, as well as the variance estimates from the precision-weighted hierarchical linear models the SEDA developers use to pool the school-subject-grade-year data into school-specific estimates of average performance and learning rates (Fahle et al., 2019).

## Results

Average test scores and learning rates vary tremendously across schools. Across the roughly 68,000 schools, the standard deviation of average performance among schools is about 1.4 grade levels. In other words, the difference in average performance between a 90$^{th}$ percentile school and a 10$^{th}$ percentile school is roughly 3.4 grade levels. Reliable learning rate estimates are available for a subset of 47,000 schools. Among these schools, the standard deviation of learning rates is approximately 0.2 such that children in a 90$^{th}$ percentile school learn, on average, 57% faster than those in a 10$^{th}$ percentile school.

Interestingly, and similar to work using district data (e.g., Reardon, 2019), the learning rate in a school is essentially uncorrelated with the average performance in the earliest grade of a school. Figure 1 provides a visualization of this weak association; the adjusted observed correlation is essentially zero (r=-0.01). Figure 1 also highlights different patterns of educational opportunity available to students across schools that are defined by the dimensions of average performance and learning rates. Schools falling in the upper left quadrant are those where students initially have low average test scores, possibly reflecting fewer early childhood or prior-grade learning opportunities, but where students learn at faster rates than the national average. In other words, these schools may be helping less advantaged students to "catch up." Schools in the lower right quadrant, in contrast, are those where students begin with relatively high average test scores and subsequently learn at slower rates during school grades.

To understand this variability, we first look at the relationship between test-score measures and school poverty rates, as measured by the proportion of students eligible for free or reduced-price lunch (FRPL). There is a strong positive association (Figure 2); the observed percent of students eligible for FRPL at a school explains around 63% of the variation in observed average test scores. Notably, FRPL rates are not deterministic of students' educational opportunities, as the figure also indicates substantial variability at any given school poverty rate. In contrast, the association between learning rates and school poverty is much weaker; the percent of students eligible for FRPL at a school explains only about 5% of the variation in average learning rates. While FRPL rate is highly predictive of students' average performance or performance when they enter school, it has little association with how much or how fast they learn. We find similar results when looking at school demographics, e.g., the percentage of black and Hispanic students enrolled in a school. Average performance is lower in schools that serve high percentages of minority students; however, learning rates are not strongly correlated with demographics.

We also explore the average performance and learning rates by school structure and type, including charters and non-charters, urbanicity, and school grade level (Table 4). Notably, this table suggests that charter schools have lower average test scores by about half of a grade level (-0.5 vs. -0.04) relative to traditional public schools and that they have higher growth rates by nearly 6% (1.092 vs. 1.035). However, these estimates are descriptive. Nonrandom selection into charter schools precludes causal interpretation of any simple differences. More work is needed to understand the implications of variation in educational opportunity by school structure.

## Conclusion

Nationally comparable measures of both student average performance and learning rates in schools reflect different dimensions of students' educational opportunity. We show that both vary significantly among schools, but that the two are essentially uncorrelated. In other words, high average performance of students in schools, on average, does not guarantee that students are also learning at faster rates.

Preliminary explorations highlight that school demographics are strongly associated with average performance but not growth, similar to what is found in district-level explorations (e.g., Reardon, 2019). Next steps for this work include exploring additional correlates of learning rates, such as proxy measures of school quality, and further exploring variation across school structures.

## References

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Tables and Figures

Figure 1. U.S. school learning rates vs. average performance

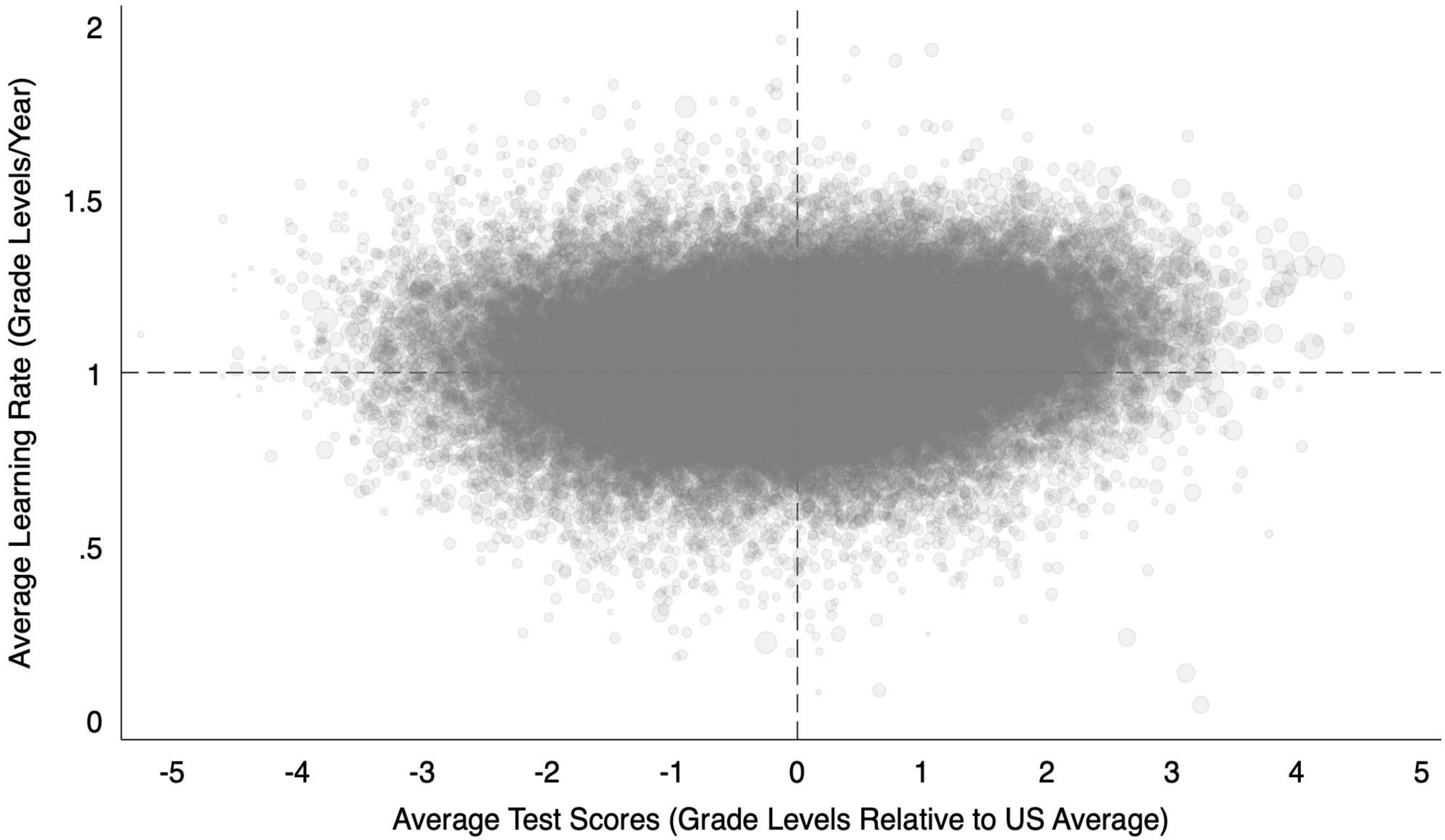

Figure 2. U.S. School Average Performance vs. FRPL Rates

Figure 3. U.S. School Learning Rates vs. FRPL Rates

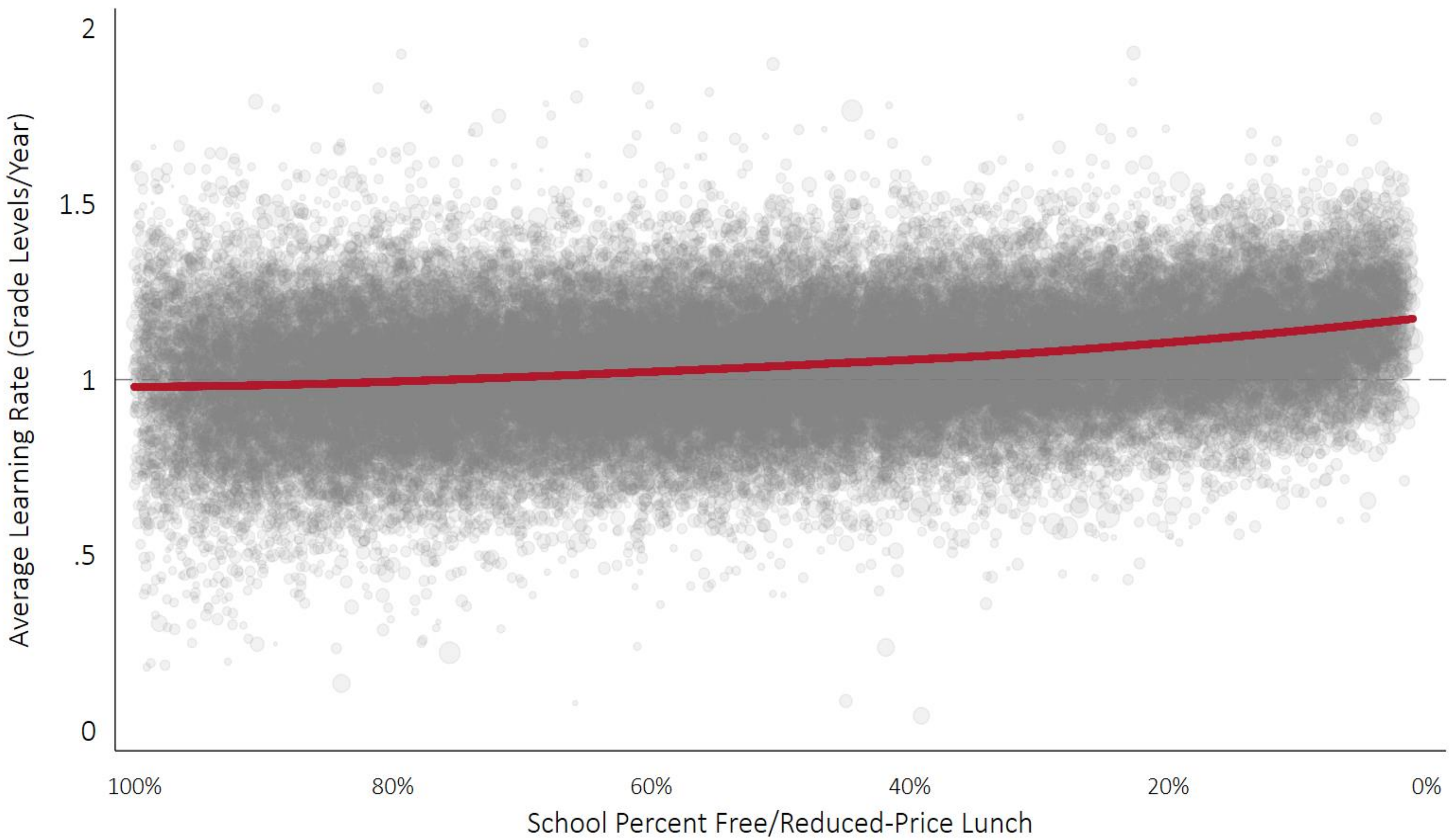

Table 1. Average Test Scores and Learning Rates by School Structure Variables

| | Average Test Scores | | | | | Average Learning Rate | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Category | N | 10th Perc. | Mean | 90th Perc. | SD | N | 10th Perc. | Mean | 90th Perc. | SD |
| All | 67917 | -1.84 | -0.08 | 1.60 | 1.35 | 46670 | 0.75 | 1.04 | 1.32 | 0.23 |
| Non-Charter | 63479 | -1.77 | -0.04 | 1.61 | 1.33 | 43968 | 0.75 | 1.03 | 1.31 | 0.22 |
| Charter | 4419 | -2.63 | -0.58 | 1.44 | 1.58 | 2698 | 0.77 | 1.09 | 1.41 | 0.26 |
| Elem. / Max Grade < 6 | 27739 | -1.45 | 0.18 | 1.80 | 1.26 | 17997 | 0.71 | 1.01 | 1.32 | 0.24 |
| Middle / Min Grade > 5 | 15454 | -2.07 | -0.22 | 1.47 | 1.40 | 7921 | 0.80 | 1.05 | 1.29 | 0.20 |
| Other Grade Spans | 24724 | -2.11 | -0.28 | 1.39 | 1.38 | 20752 | 0.77 | 1.06 | 1.33 | 0.23 |
| City | 18274 | -2.52 | -0.60 | 1.46 | 1.56 | 13342 | 0.72 | 1.03 | 1.33 | 0.25 |
| Suburb | 21782 | -1.45 | 0.36 | 2.07 | 1.36 | 16258 | 0.77 | 1.05 | 1.32 | 0.22 |
| Town | 8005 | -1.59 | -0.23 | 0.99 | 1.05 | 5009 | 0.76 | 1.04 | 1.31 | 0.22 |
| Rural | 19837 | -1.31 | -0.02 | 1.21 | 1.04 | 12057 | 0.77 | 1.04 | 1.30 | 0.22 |