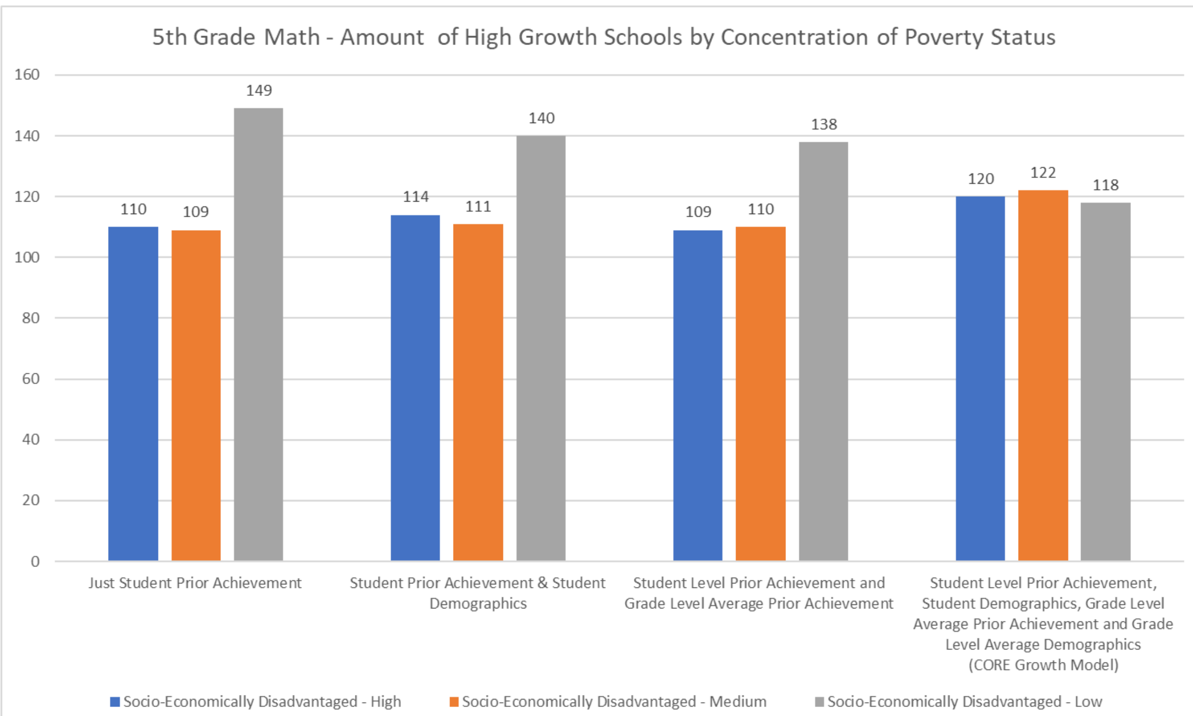
Analysis of Residual Gain Student Level Growth Models
May 2018

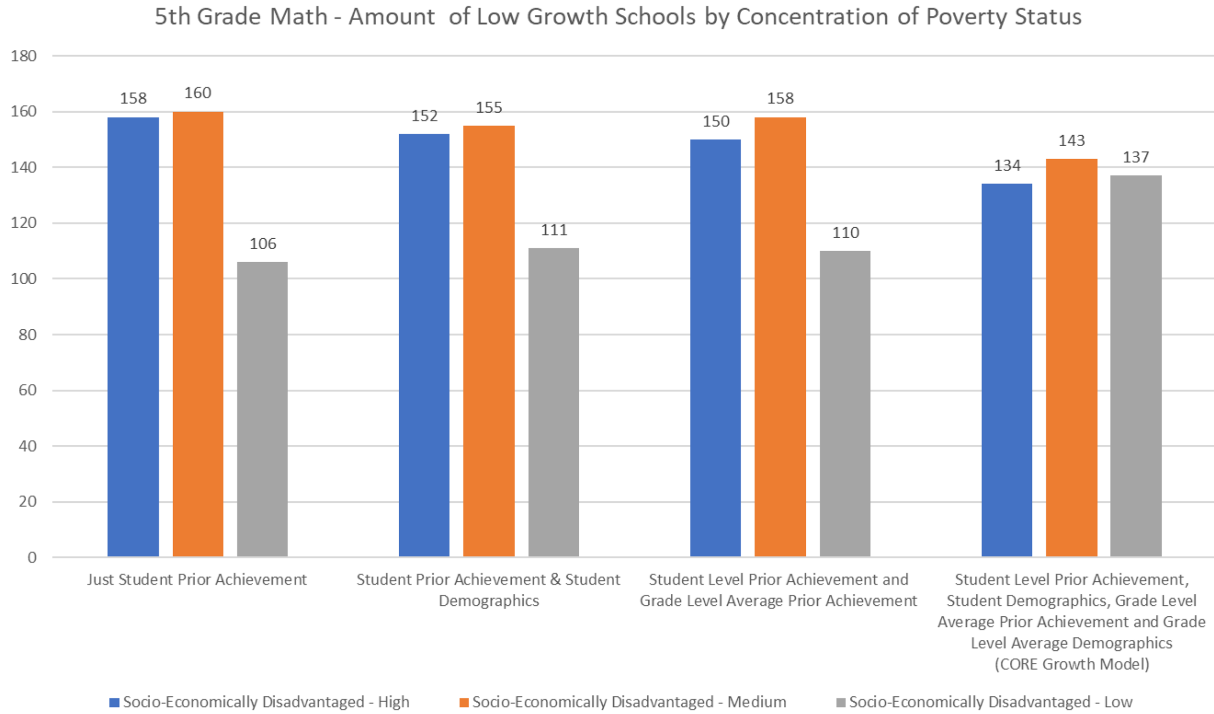
CORE recently conducted an analysis of various residual gain student level growth models for all schools in the CORE Data Collaborative, which represents roughly one quarter of the schools in California. The analysis is based upon 2015-16 and 2016-17 SBAC scores. We found that ***only a residual gain growth model that controls both for student prior achievement and for peer effects – especially the peer effects of being in a school with concentrated poverty -*** evens the playing field enough to show equal gains for schools serving large numbers of LCFF targeted students.

As illustrated in the following two charts[1], without leveling the playing field with respect to poverty, California's dashboard will under-identify high growth/high poverty schools and over-identify low growth/high poverty schools.



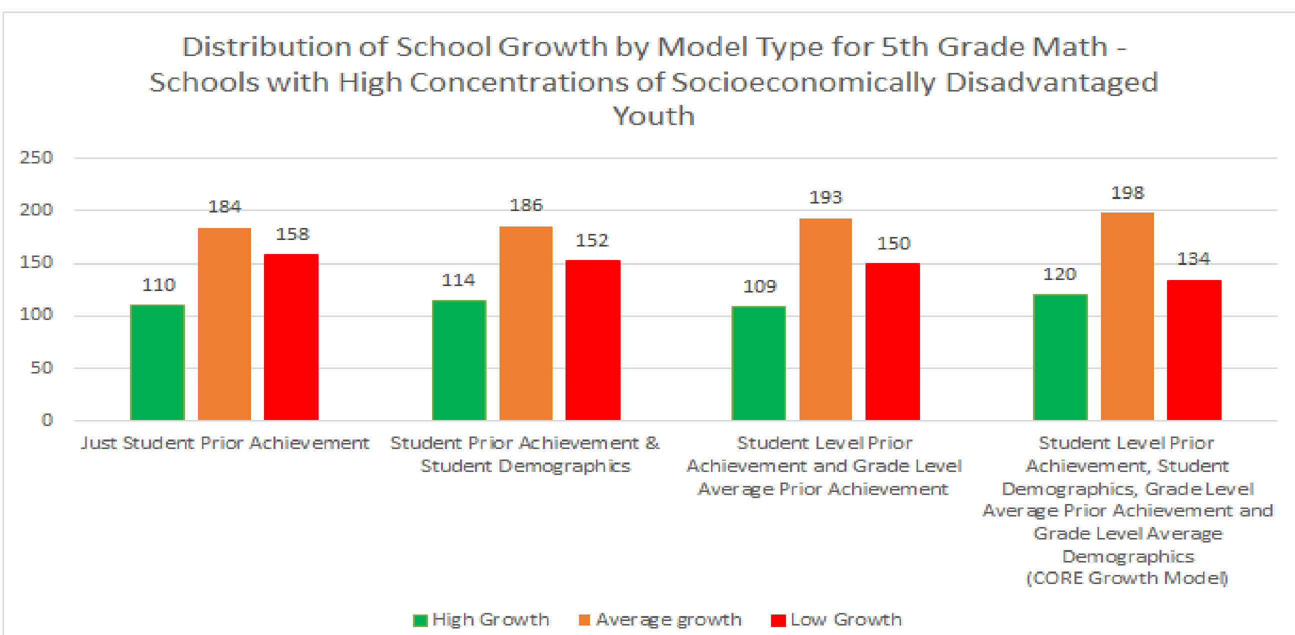
Only the model on the right – the one that controls for student-level and peer-level prior achievement and demographics – results in a fairly even distribution of schools identified as high growth amongst schools that are at high, medium and low concentrations of poverty.

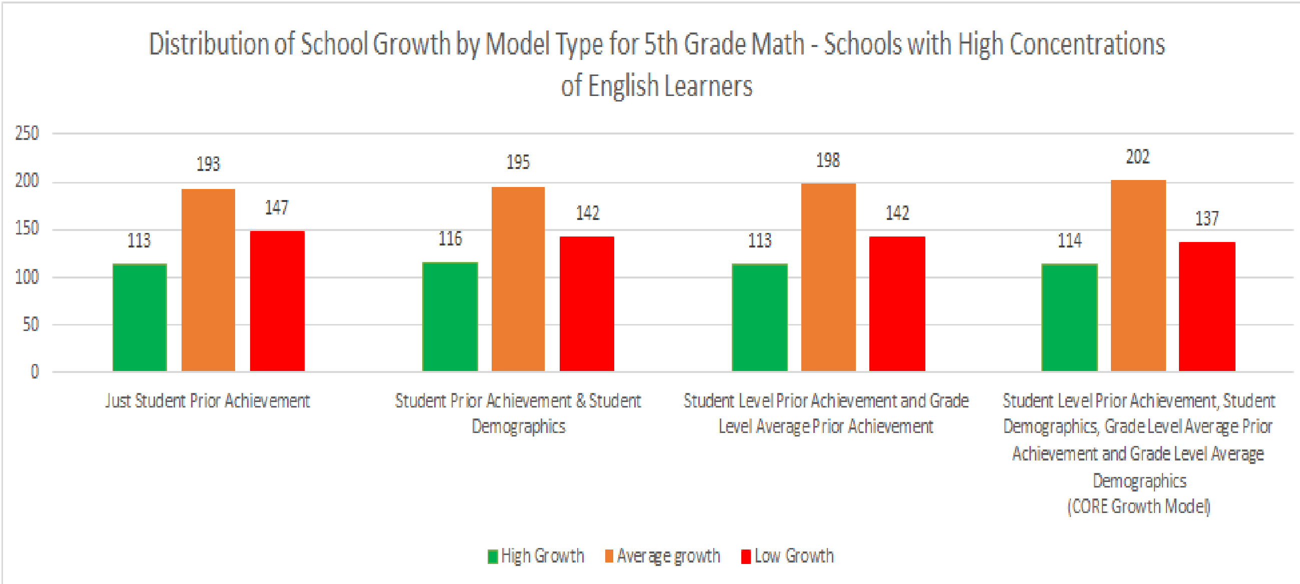
[1] All models utilize prior year and year in question scale scores from the SBAC assessments. Models that include demographics include the following demographics – socioeconomically disadvantaged status, English Learner status, homeless status, disability status and foster status.



The chart above shows that only the approach used on the right results in a relatively even identification of which schools are achieving the lowest levels of growth.

Also, the following two charts illustrate the distribution of schools serving large populations of socio-economically disadvantaged students and English learners using 5th grade math scores among various growth models. As evidenced in the charts, the number of schools identified as having low, average and high growth varies greatly depending on the model.

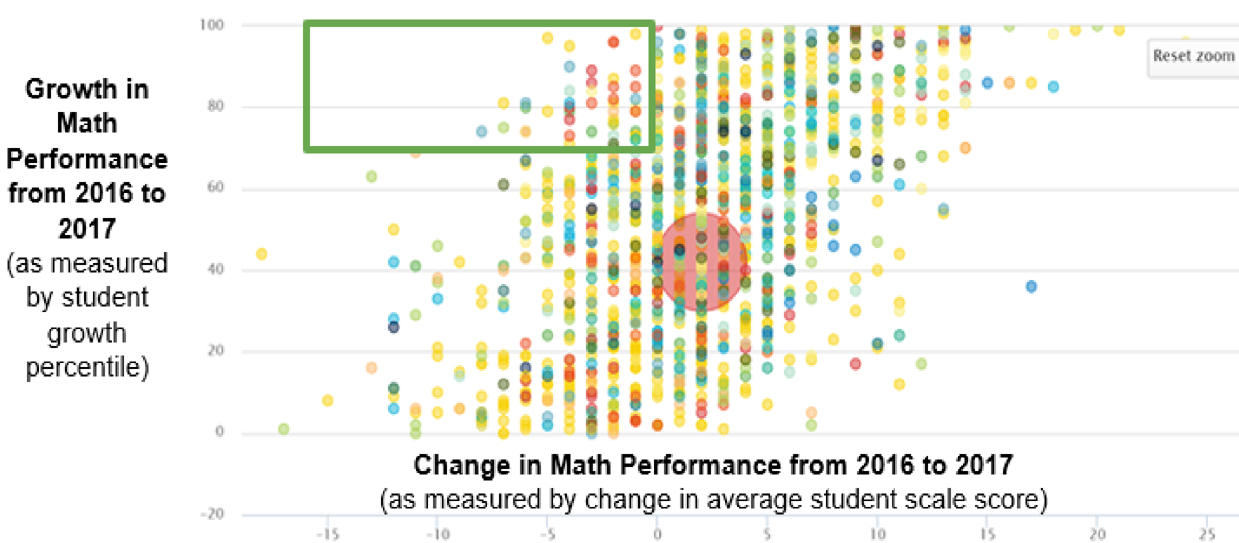




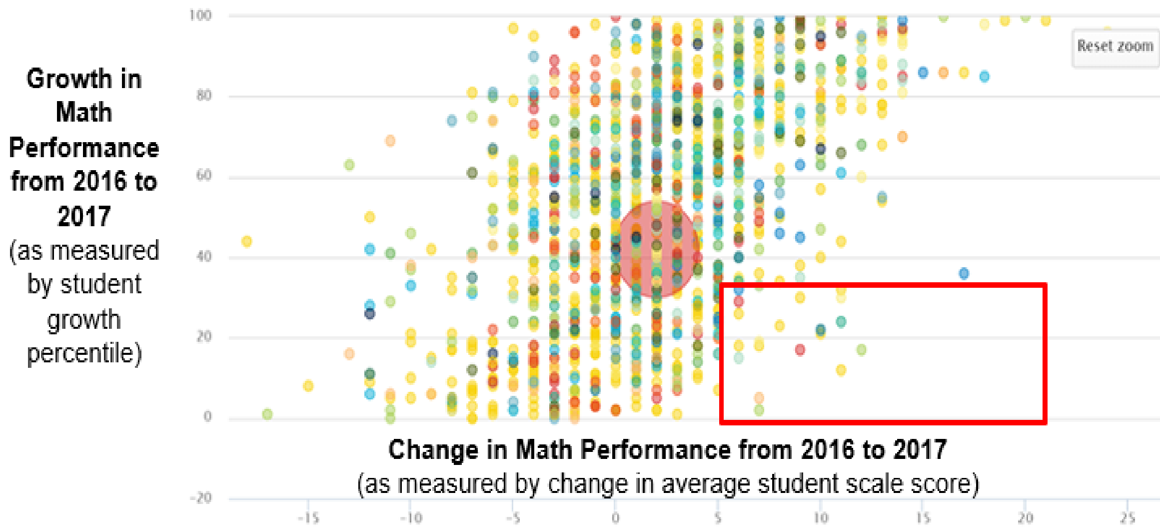
The model on the right is more finely-tuned to identify the schools serving large populations of socio-economically disadvantaged students and English learners that are having the greatest impact on student learning.

Meanwhile, we understand there continues to be misunderstanding about change versus growth, and it will take time to build awareness and understanding. A finely-tuned growth measure will be an important tool for educators, stakeholders and parents because it highlights impact, and it is substantially different than other existing indicators on the California school dashboard.

The chart below shows that among schools with negative year-to-year change, a substantive number of schools are high growth. For these negative change, high growth schools, treating change as impact will lead to mistaken interpretations. These schools are actually having a strong impact on student level growth but due to differences in student populations in 2016 versus 2017 the change is negative.



Conversely, the chart below shows among schools with positive year over year change, many have low growth. For these positive change, low growth schools, treating change as impact also will lead to mistaken interpretations.



In addition to high level policy decisions such as which type of growth model to use and what to include as control variables, there are a number of highly technical actions that are well vetted by other states and districts, as well as the research community that deserve attention. These include such things as transforming scale scores into standardized units to facilitate comparability across grade levels; incorporating known error levels in the underlying tests; how to treat outliers; transforming the output of the growth model into a shareable measure; and aggregation of growth across grade levels. An independent review of these technical specifications by a small panel of experts in residual gain growth models would benefit California's ultimate approach.

Note: For this analysis, CORE and Education Analytics (EA) ran a school level growth model with two samples of data: one with just the CORE Data Collaborative and then another with all California schools. In this model, the outcome variable is the 2017 average school-level scale score and the predictor variable is the 2016 average school-level scale score. EA ran the model by subject (ELA and Math) and by grade (grades 4 through 8). EA found that prior achievement had a substantively similar predictive relationship on model outcomes between the CORE and statewide samples. For example, in grade 5 math, growth estimates for schools in the core data collaborative do not substantively change and are correlated at .99 between the two models. This suggests that the growth patterns of students in CORE Data Collaborative is essentially the same as growth patterns throughout California.