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Summary of Median Growth Percentile Analyses: Descriptive Statistics, Demographics Correlations, and Stability Analyses

Benjamin R. Shear

A report prepared by the Center for Assessment, Design, Research and Evaluation (CADRE) at the CU Boulder School of Education.

School of Education
UNIVERSITY OF COLORADO BOULDER

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About CADRE

The Center for Assessment, Design, Research and Evaluation (CADRE) is housed in the School of Education at the University of Colorado Boulder. The mission of CADRE is to produce generalizable knowledge that improves the ability to assess student learning and to evaluate programs and methods that may have an effect on this learning. Projects undertaken by CADRE staff represent a collaboration with the ongoing activities in the School of Education, the University, and the broader national and international community of scholars and stakeholders involved in educational assessment and evaluation.

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Please direct any questions about this project to:
Benjamin.Shear@Colorado.Edu

Table of Contents

Executive Summary

Given the importance of the academic growth measures used in School Performance Framework (SPF) accountability ratings, it is necessary to understand properties of these metrics. This report describes a series of analyses to investigate school-level median growth percentiles (MGPs), focusing on the following questions:

1. How much do school-level MGPs vary across schools, and has this variation remained constant across time?
2. To what extent are school-level MGPs correlated with current student achievement, prior student achievement, and current school demographic characteristics? How do these correlations compare to the correlation between current average achievement and the same demographic variables?
3. How much of the variability in school MGPs can be explained by school demographic variables?
4. How stable are school MGPs from year to year?

Key findings presented in detail throughout the remainder of the report are as follows.

- Based on descriptive analyses of the distribution of school-level MGPs at the overall school level and separately for elementary (4-5) and middle school (6-8) grades, in mathematics the distribution of MGPs remained relatively constant from 2009-2014 and in 2016 and 2017. The variability in middle school math MGPs decreased steadily, but not substantially, during this time period. In English Language Arts (ELA), however, MGPs across schools were substantially more variable in 2016 and 2017 than they were for the years 2009-2014, when the variability remained relatively stable. There is not a clear-cut explanation for these changes, and they would be worth investigating in future studies.
- Within-year correlations between school-level MGPs and prior average achievement ranged from approximately 0.2-0.3, which were substantially lower than correlations between current average achievement and prior average achievement, which were generally above 0.90. This is true across all school levels, years, and subjects. The same is true for aggregate school demographics, including the percent of white students in a school, percent of students eligible for free or reduced-price lunch (FRL), the percent of students identified as English Language Learners (ELL), and the percent of students with an Individualized Education Program (IEP). The correlation between school MGPs and the percent of students eligible for FRL was about -0.20 or lower across subjects and school levels, and this was the demographic variable most highly correlated with MGPs. In contrast, the correlation between average achievement and the percent of students eligible for FRL was generally between -0.7 and -0.8 across subjects and school levels. Although MGPs are much less closely associated with these student demographic characteristics than are average test scores, however, school MGPs are still correlated with prior achievement and student demographics. This happens because there is nothing in the process of calculating MGPs that would completely remove this correlation.

- To quantify the difference in the strength of association between average test scores and demographics versus MGPs and demographics, we use multiple regression models that attempt to predict a school's average test scores or MGP in a given year based on the percent of students identified as ELL, percent of students eligible for FRL, and the percent of students identified as white. While these three variables can explain approximately 50-70% of the variability in average test scores, they explain only approximately 2-10% of the variability in school MGPs. Including school prior year average scores in the model explains over 90% of the variability in current year school average scores, but only 10-20% of the variability in school MGPs.
- The use of MGPs in the SPF ratings assumes that school MGPs across years should be positively associated, but not perfectly associated. From 2009-2014, MGPs had moderate to strong positive correlations from one year to the next, with adjacent-year correlations ranging from 0.46 to 0.63 across subjects and grade levels. The correlations between MGPs from 2016 to 2017 were lower than in earlier years, ranging from 0.36 to 0.57. MGPs in mathematics were more highly correlated across years than MGPs in ELA.
- The results were generally consistent with claims made about school MGPs regarding the associations between MGPs and demographics and the stability of MGPs across years. However, the results also raise some additional questions, including: the change in the distribution of ELA MGPs, the small but non-zero association between MGPs and demographics or prior achievement, and potential factors that could explain the variability of MGPs both between and within schools.
- Lastly, we note that, while relevant to evaluating the uses and interpretations of MGPs in the SPF system, these results do not constitute a complete evaluation or validity argument to support the use of MGPs as a school accountability metric.

Introduction

Student achievement data, in the form of average scale scores and median student growth percentiles (MGPs) based on state assessments, form the core elements of Colorado's annual school and district accountability ratings. Each year schools receive a performance rating as part of Colorado's School Performance Framework (SPF) accountability system[1]. For middle and elementary schools, student academic growth, as measured by MGPs, makes up 60% of SPF accountability ratings, while current year academic achievement, as measured by average scale scores, makes up the remaining 40% of a school's rating. For high schools, MGPs account for 40% of the rating, while average achievement test scores and postsecondary and workforce readiness indicators each make up 30% of the ratings.

The annual rating a school earns has important implications for the school. The results are reported publicly and are used to determine the type of improvement plan the school is required to enact in subsequent years. In the most extreme cases, the State Board of Education (SBE) can require a school to be closed or converted to a charter school. Current professional standards in the field of educational measurement require that inferences or decisions based on test scores, such as those in the SPF, be supported with both theoretical and empirical evidence

[1]For more information see https://www.cde.state.co.us/accountability/performanceframeworks.

through a process known as validation (AERA, APA, & NCME, 2014).

This document presents descriptive analyses of school-level MGPs in Colorado, drawing on nearly a decade of historical MGP data from 2009 – 2017. These analyses were conducted by the Center for Assessment, Design, Research & Evaluation (CADRE) at the University of Colorado Boulder School of Education, at the request of the Colorado Department of Education (CDE). These analyses do not provide a comprehensive evaluation of the use of MGPs for school accountability. Rather, these descriptive analyses are intended to provide one source of information for CDE and other stakeholders to consider when evaluating MGP uses and interpretations as part of the SPF accountability system.

Background

Student growth percentiles (SGP; Betebenner, 2009) are descriptive statistics that characterize a student's performance on a standardized test relative to other students who earned similar scores on prior tests. More specifically, an SGP answers the question, "among students with similar scores on prior tests, what proportion of students earned a lower score on this year's test?" A student with an SGP of 65, for example, scored higher on this year's test than 65% of students who had similar scores on prior tests. SGPs are sometimes referred to as "conditional status metrics," because they describe a student's current achievement (i.e., "status" as measured by a standardized test), relative to other students with similar academic histories (i.e., "conditional on" their prior test scores). SGPs thus provide a norm-referenced way to contextualize and interpret a student's current-year test score.

Median student growth percentiles (MGPs), representing the median SGP earned by students at each school, are included in school accountability ratings to provide an alternative metric of student learning relative to that provided by average achievement. MGPs attempt to "level the playing field" when making comparisons across schools by capturing how much student scores improve during the year, not only where they end up, and comparing that change to other students with similar scores in prior years. One rationale for using growth measures to identify schools in need of further support is that MGPs are expected to be less highly correlated with student demographic variables. The Colorado Technical Advisory Panel for Longitudinal Growth (TAP; https://www.cde.state.co.us/accountability/tap) writes, "Because growth is more sensitive to the year to year changes in how students perform and is much less strongly related to school demographics than achievement, it is arguably a fairer accountability indicator than achievement" (TAP, 2019). This is a claim that can be evaluated empirically by comparing the association between average achievement and demographics relative to MGPs and demographics. A lack of association between MGPs and school demographics on its own, however, is not enough to justify the use of MGPs in the accountability system. If growth ratings were randomly assigned to schools, for example, these would be uncorrelated with school demographics, but also indefensible as accountability metrics.

Another important assumption underlying the use of MGPs in the accountability system is that schools will earn similar, but not identical, MGP ratings across years. Because MGPs are sensitive to instructional and other practices within schools, a school's MGP is expected to vary somewhat from year to year. According to the TAP, "Because they are based on growth in a single year, SGPs are sensitive to year-to-year changes in school practices" (TAP, 2019). As a result, MGPs, which are aggregates of SGPs, should also be sensitive to these changes. If this is true, then one would expect that a school's MGP should vary from year to year.

On the other hand, if school MGPs are very unstable from year to year, this can raise at least two problems. First, from a theoretical standpoint, if MGPs reflect something about how effective a school is at supporting student learning, one would expect that schools that are more effective in one year are likely to be more effective the following year. Second, from a practical perspective, large variability in MGPs from year to year undermines their use to "Identify schools and districts for additional support based on student academic outcomes" (TAP, 2019). Supports provided in the current year will necessarily be based on MGPs from the prior academic year, because MGPs and resulting SPF ratings are released in the late summer or early fall. The assumption is that schools with relatively low MGPs in the prior year are the same schools that would benefit from additional supports in the upcoming year. But if a school's MGPs vary widely from year to year, then providing additional supports to schools in the current year that earned low MGPs in the prior year may not be appropriate. Using the multiple years of MGP data available in Colorado, patterns in the annual variability can also be evaluated empirically.

Before describing the data and methods used to provide empirical evidence about these assumptions, we briefly describe some relevant prior conceptual and empirical research.

Related Literature

Although academic growth measures that account for prior achievement are generally less highly correlated with school demographic factors such as student poverty rates or student race and ethnicity, there are multiple reasons school-level growth measures based on SGPs could still be correlated with student demographics. Because SGPs do not directly take into account student demographic variables, there is no guarantee that either student-level SGPs or school-level MGPs will be uncorrelated with student demographic variables (Ehlert, Koedel, Parsons, & Podgursky, 2016). School MGPs could be correlated with student demographics either because there are true differences in educational opportunity across schools that is associated with demographics, or due to statistical artifacts such as bias caused by measurement error in student test scores (McCaffrey, Castellano, & Lockwood, 2015; Shang, VanIwaarden, & Betebenner, 2015). If MGPs are correlated with school demographics because there are true differences in what students are learning across schools, this may call into question whether their use truly levels the playing field but does not necessarily invalidate MGPs as measures of student learning for an accountability system. If MGPs are correlated with school demographics because measurement error in the student test scores used in the SGP model causes bias in SGPs and MGPs, this would undermine the use of MGPs as measures of student learning.

There is relatively little prior research about the magnitude of the associations between student demographic characteristics and MGPs at the school level. Using data from Colorado in 2004-2006, Briggs and Betebenner (Briggs & Betebenner, 2009) report correlations with school-level MGPs and the percent of students eligible for free or reduced-price lunch (FRL) that ranged from -0.25 to -0.42, depending upon the year, and from -0.18 to -0.31 when analyzing data at the school-by-grade level. Ehlert et al. (2016) report a correlation of -0.37 between a 5-year school-level MGP and the percent of FRL eligible students at each school, using data from Missouri in 2007-2011. These prior analyses suggest that there is likely to be some association between school demographics and MGPs, although the causes and exact magnitude or direction can be hard to determine a priori.

Regarding the variability of MGPs across years, McCaffrey et al. (2009) and Kane and Staiger (2002) describe three factors that contribute to differences in school-level achievement measures such as MGPs within and between schools: sampling error, non-persistent effects, and persistent effects. First, there can be sampling error caused by idiosyncrasies or measurement error in individual student test scores each year. A student might guess luckily (or unluckily) on a few questions, earning a higher or lower score due to chance, which in turn would affect their SGP and hence the school's MGP. This source of variability will have a greater impact on schools with fewer students, where each student's SGP has a greater effect on the aggregate MGP.

Second, there can be non-persistent school-level factors that vary from year to year, causing a school's MGP rating to vary from year to year. A certain cohort of students might be particularly engaged (or disengaged) throughout the year, there could be a disruption during the school year or testing period, or a school could make instructional or curricular changes. While these factors could cause MGPs to be higher (or lower) and truly reflect the fact the students did learn more (or less) in a given year, the influence of these factors would not necessarily be expected to persist or continue in subsequent years. Systematic trends of increasing or decreasing MGPs across time would also contribute to non-persistent effect variance.

Finally, persistent factors such as instructional or other practices that a school enacts consistently from year to year, or characteristics of student cohorts that remain constant, would lead to consistently higher levels of student learning and hence higher MGPs in some schools relative to others. While these persistent effects cause differences in MGPs across schools within a given year, they do not contribute to variability of MGPs across years within a given school.

Calculating the correlation between school-level MGPs across years can help determine the extent to which school MGPs reflect persistent versus non-persistent factors. If sampling error or other non-persistent factors have relatively little effect on MGPs, school MGPs should be highly correlated across years; if these non-persistent factors have a large influence on school MGPs, school MGPs will be less highly correlated across years. Under certain assumptions, McCaffrey et al. (2009) note that the correlation of aggregate performance measures across adjacent years can be used to approximate the percent of variation in MGPs that is due to persistent effects rather than non-persistent effects or sampling variance. One large comparison of different school-level growth metrics, reported correlations of MGPs between adjacent years ranging from 0.32 to 0.46 (Goldschmidt, Choi, & Beaudoin, 2012). For MGPs calculated at the teacher level, correlations across adjacent years were 0.59 for Math and 0.43 for Reading in one report (Goldhaber, Walch, & Gabele, 2014) and ranged from 0.50 to 0.54 in another (Pivovarova & Amrein-Beardsley, 2018). These are similar to, but generally higher than, the year-to-year correlations of teacher-level value-added model (VAM) scores reported by McCaffrey et al. (2009) of 0.2-0.5 for elementary and 0.3-0.6 for middle school teachers. Although it is not possible to specify what the "correct" or "optimal" year-to-year correlation among MGPs should be, the theoretical rationale from the TAP suggests they should be at least moderately positively correlated. These prior studies provide an approximate range that might be expected.

The next section provides more detail about how the MGP data were used to provide empirical evidence relevant for considering these issues.

Methods

Using an extensive database of historical SGP data in Colorado, we report descriptive analyses relevant to evaluating the extent to which MGPs are correlated with school demographics and the extent to which school MGPs are stable across years.

We first provide summary statistics that describe the distribution of MGPs, by subject, year, and school grade levels. Next, we summarize the correlation between school demographics and MGPs, again by subject, year, and school grade levels. We compare these correlations to the correlation between average test scores and the same demographic variables. In addition to reporting correlations, we also use multiple regression models to estimate the amount of variability in MGPs and average test scores that can be explained by school demographics. Finally, we summarize the correlations of school MGPs across years, separately by subject and school grade level.

Data

The data in these analyses were supplied by the CDE. The data include grade 4-10 Math and Reading test scores in the years 2009-2014 and grades 4-8 Math and ELA test scores in the years 2016-2017. We refer to both Reading and ELA scores as “ELA.” We drop all 2015 data from the analyses, due to the test transition that occurred during this year, and at the request of the CDE. The data also include student demographic information described below. In 2016 and 2017, high school data are dropped from the analyses due to ongoing changes in the tests used. Thus, the data include CSAP and TCAP MGP data for grades 4-10 in the years 2009-2014, and grade 4-8 CMAS MGP data for 2016 and 2017. No 3rd grade data are included in these analyses because SGPs cannot be computed for students in 3rd grade, as 3rd grade is the first grade in which students take state tests (and hence no prior scores are available for computing SGPs). Note, however, that 4th grade SGPs are computed using 3rd grade test scores. The Appendix describes the data processing steps used to construct the final sample.

Unit of Analysis

In this document we report results aggregated either at the overall school level or at the EMH level (where “EMH” stands for Elementary/Middle/High School designation). Aggregation at the overall school level, which is referred to as an EMH level of “All” below, is based on aggregating SGPs and other variables across all students in a school with valid scores in the grades and subjects for which SGPs are calculated. Aggregation at the EMH levels is based on aggregating SGPs and other variables across all students with valid scores at a school for the Elementary (grades 4-5), Middle (grades 6-8), or High School (grades 9-10) grades separately. If a school enrolls students in 1st through 8th grade, for example, the analyses at the overall school level would be based on students in grades 4-8, while the EMH results would aggregate the results for students in grades 4-5 and treat them as a separate unit from results aggregated for students in grades 6-8. We use the CDE school number and EMH code variables to define these units. For the purposes of the SPF accountability ratings, results are generally aggregated at the EMH level.

MGP Calculations

There are a number of different decisions that can be made when computing SGPs and MGPs, including whether to correct for measurement error in student test scores and the number of prior year scores to utilize. The analyses presented here use the SGPs provided by CDE, which are the SGPs used operationally for state accountability purposes. Here we briefly outline some characteristics of the operational SGPs used in Colorado.

- As noted above, when aggregating SGPs to the school level we use the median SGP rather than the mean SGP. This is for consistency with the type of aggregate SGP used in the Colorado accountability frameworks.
- The SGPs calculated in Colorado from 2009-2014 used all available prior test scores for each student, which could have been at most 3rd-9th grade prior test scores for students in 10th grade. For the SGPs computed in 2016 and 2017, however, only scores from tests administered in 2015 or later were used in the computations of SGPs.
- The coefficient matrices used to calculate SGPs are “re-normed” each year, rather than fixed to an established baseline.
- No correction for measurement error in student test scores is used when calculating SGPs.
- For any school or EMH unit with fewer than 20 valid SGPs in a given year, no MGP is reported and the school is not included in the MGP or other analyses reported here for that year. This follows the accountability reporting rules used by CDE.

Additional Variables

In addition to the MGPs for each school or EMH unit, we also calculate the following additional aggregate achievement and demographic variables. Test scores are first standardized within grade, year, and subject (using the overall statewide means and standard deviations) before constructing these aggregate variables. Within each year the sample is limited to students enrolled grades 4-10 (in 2009-14) or grades 4-8 (in 2016-17) with a valid scale score. Although most students with a valid scale score in these grades also have a valid SGP, some students with a valid scale score may not have an SGP if, for example, they do not have valid prior year scale scores. All students with a valid SGP must have a valid scale score, and hence the number of students with valid scale scores can be larger than the number of students with a valid SGP in some schools.

School average current achievement: this is the average test score, by subject, for all students with a valid scale score in a grade for which SGPs are calculated (e.g., we do not include 3rd grade test scores when computing the average test score, because students in 3rd grade do not have SGPs).

School average prior achievement: this is the school-level average test score in the prior year for each school or EMH unit (again, averaged after standardizing student scores by grade, year, and subject and only for students in grades that have SGPs).

Student average prior achievement: this is the average student-level prior year scale score for all students currently enrolled in a school or EMH unit in a grade with SGPs. This value differs slightly from the average school prior achievement described above, although they are often similar. In this case, 3rd grade scores are represented for students currently enrolled in 4th grade.

Demographics: We also calculate the following demographic characteristics for each school or EMH unit, based on all students with a valid current year scale score:

- Percent of students reaching the “proficient” cut score on the test,
- Percent of students whose race was identified as white,
- Percent of students who were eligible for free or reduced price lunch (FRL),
- Percent of students who were identified by CDE as English language learners (ELL),
- Percent of students identified by CDE as having an individualized education program (IEP; only available in 2013 and later years), and,
- Percent of students who identified as female.

Results

Distribution of MGPs

Table 1 reports the number of schools with MGP data along with the mean and standard deviation of MGPs across schools at the overall school level and EMH levels. At the overall school level there are between 1,316 and 1,616 MGP observations per subject and year; at the Elementary level there are between 975 and 1,004 per year; at the Middle school level there are between 455 and 510; and at the high school level there are between 318 and 350. There are fewer schools with MGPs at the overall level in 2016 and 2017 for two reasons. First, we do not use the high school (grade 9 and 10) MGPs in 2016 and 2017 so the sample no longer includes schools that enroll only high school students. Second, beginning in 2015 some students' parents opted them out of state testing, which in turn reduced the number of test scores and SGPs, dropping the SGP sample size below 20 for some additional schools and EMH units.

Table 1. MGP Summary Statistics by Subject, School EMH Level, and Year.

		All School Level			Elementary School			Middle School			High School		
Subject	Year	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
ELA	09	50.5	9.4	1573	50.2	10.0	976	50.2	9.6	455	50.9	9.9	318
ELA	10	50.0	10.0	1579	49.9	10.6	974	49.5	10.2	469	51.2	9.4	323
ELA	11	50.6	9.5	1581	50.3	10.0	983	50.5	9.8	471	51.8	10.7	325
ELA	12	50.6	9.4	1592	50.3	10.0	990	50.4	9.5	497	52.3	10.5	331
ELA	13	50.3	9.2	1604	49.9	9.9	1000	50.3	9.3	501	51.4	10.0	333
ELA	14	50.3	9.2	1614	49.8	10.1	996	50.2	9.0	509	52.1	9.3	350
ELA	16	50.7	11.9	1318	50.5	12.1	995	50.8	13.1	482	--	--	--
ELA	17	50.6	12.1	1337	50.5	12.1	1004	50.6	13.4	501	--	--	--
MATH	09	50.0	12.2	1575	50.3	12.9	976	49.1	13.3	455	49.5	11.9	320
MATH	10	50.3	12.6	1582	50.1	13.3	975	49.7	13.7	469	51.8	10.8	323
MATH	11	50.4	11.8	1584	50.0	12.3	982	49.8	13.0	471	52.2	11.2	325
MATH	12	50.4	12.1	1592	50.3	12.7	992	49.5	13.3	499	51.3	12.0	330
MATH	13	50.0	11.8	1605	49.9	12.3	1000	49.2	12.9	501	51.3	11.8	333
MATH	14	50.3	11.7	1616	50.1	12.7	997	49.4	12.2	510	52.6	11.5	350
MATH	16	50.3	12.0	1316	50.1	13.0	995	50.5	11.5	483	--	--	--
MATH	17	50.6	12.0	1337	50.5	12.8	1004	50.9	11.8	501	--	--	--

As anticipated, the average MGP is very close to 50 across all years, subjects, and EMH levels. The averages differ from 50 the most at the high school level. Histograms of the distribution of MGPs across schools (not pictured here) show that MGPs are approximately normally distributed across schools or EMH units within years and subjects. The variability of math MGPs across schools remained relatively constant across years and EMH levels, although there was a steady decline in the variability of middle school math MGPs from 2009 to 2016.

There was a noticeable increase in the variability of ELA MGPs when transitioning from the 2009-14 period to the 2016-17 period, both at the overall school level and for elementary and middle schools (high school data are not reported for 2016-17 here and cannot be compared). At the overall school level from 2009 to 2014, for example, the average within-year standard deviation of ELA MGPs across schools was approximately 9.5 points. This suggests that while the average MGP was approximately 50.5, schools deviated above or below this average value by about 9.5 points on average. In 2016 and 2017 the average MGP remained the same, but the standard deviation increased to approximately 12 SGP points, an increase of approximately 25% (the associated increase in the average variance was approximately 60%). Similar changes were observed at the elementary and middle school levels, with a slightly smaller increase in variability at the elementary level and a somewhat larger increase at the middle school level.

These changes are shown graphically in Figure 1. Figure 1 plots the mean, median, 10th percentile, and 90th percentile of the MGP distributions by subject and EMH level. Each panel shows summary statistics for a single subject-by-EMH level combination. The figure shows the relatively constant mean and median of the MGPs across years and subjects, as well as the relatively constant 10th and 90th percentiles in math. The jump in the 90th percentile and drop in the 10th percentile for the ELA MGPs is also apparent in 2016 and 2017. Because the variability in math MGPs was larger than the variability of ELA MGPs in 2009-2014, the variability of ELA MGPs in 2016 and 2017 was more similar to the variability of the math MGPs. Figure 1 also includes dashed lines at 35, 50, and 65, the values used to calculate SPF points based on MGPs, which indicate that the 10th and 90th percentile of the ELA MGPs were closer to these cutoffs in the later years.

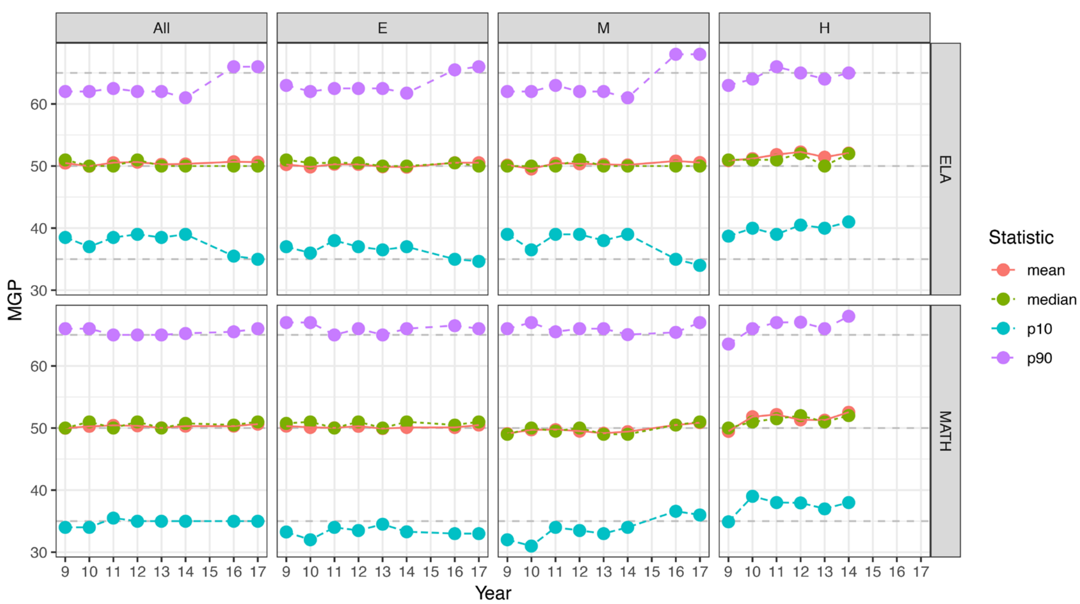

Figure 1.
Mean, Median, 10th, and 90th Percentile of MGPs Across Years, by Subject and EMH Level.

To evaluate whether the change observed could be due to the change in the sample of schools with adequate sample sizes to report MGP data in 2016 and 2017, the same summary statistics were computed only for schools or EMH units with data across all eight years. The same patterns were observed, with math MGP variability remaining roughly constant and a large increase in the ELA MGP variability in 2016-17. The Appendix includes these additional results. Inspection of the distributions of MGPs within each year also did not suggest that the increased variance was due to a small number of "outlier" schools with extreme MGP values.

While there is no clear explanation for the change in the variability of ELA MGPs across schools based on the more recent test score data, there are a few important changes that took place from 2014 to 2016 that could be related to the observed changes. First, SGPs in 2016 and 2017 were based on fewer prior year test scores – only 1 prior year for 2016 and at most 2 prior years for 2017. If SGPs estimated with fewer prior year test scores are more variable, then this could also lead to more variability in school MGPs. We note, however, that although the same change in the number of prior scores occurred for the math SGPs, there was no associated change to the variability of school math MGPs. Second, there were on-going changes made to the content and format of both the math and ELA state tests from 2015 through 2017 relative to the tests used in 2009-2014. It is possible that these changes affected SGP calculations, the evaluation of student learning, or school instructional practices in unique ways in ELA relative to math. These changes would be worth exploring further. Continuing to monitor whether the variability of ELA MGPs continues to change or remains stable will be an important consideration moving forward.

Correlations of MGPs with Student Demographics

This section summarizes the observed correlations between school MGPs, current/prior average achievement, and school-level student demographic variables. Figure 2 presents the average correlations, across years, between school MGPs or average test scores and each of the following additional variables at the overall school level: change in school average scores from prior to current year (mean_change), percent of students reaching the proficient benchmark (pct_prof), school prior year average score (mean_prior_sch), student prior year average score (mean_prior_stu), percent of white students (pct_white), percent of female students (pct_female), percent of students classified as ELL (pct_ell), percent of students with an IEP (pct_iep), and percent of students eligible for FRL (pct_frl). Each panel shows correlations based on either ELA or math test scores. Within each panel, the blue triangles show the average correlation (across years) between MGPs and the indicated variable, while the red circles show the average correlation between average scale scores and the indicated variable. The variables are arranged in order based on the magnitude of the average correlation with MGPs. These correlations varied relatively little across years.

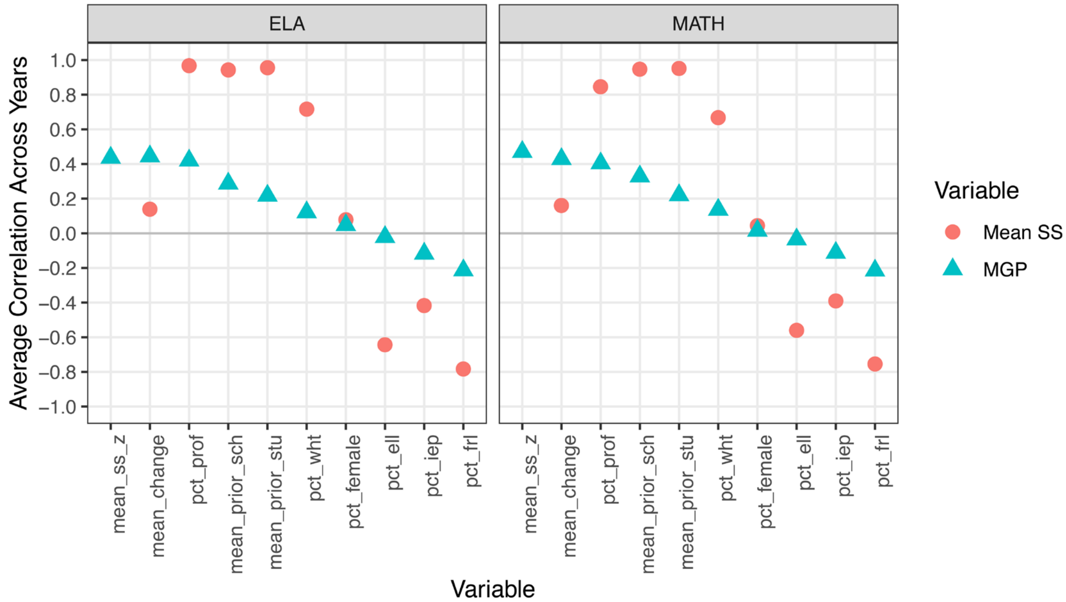

Figure 2. Average Correlations between MGP or Current Mean Scale Score and Demographic or Achievement Variables, All School Level.

Figure 2 shows that MGPs are consistently less correlated with the various status measures of achievement and with student demographic variables than are average scale scores. Both ELA and math MGPs are correlated at about 0.4-0.5 with current year average scale scores (mean_ss_z), the change from prior to current year average scale scores (mean_change), and the percent of proficient students (pct_prof). The correlation between MGPs and school prior year average (mean_prior_sch) or student prior year averages (mean_prior_stu) are even lower. In contrast, the current year scale score is nearly uncorrelated with the change in average scale score from the prior to current year (correlation of about 0.15), but is highly correlated with the percent of proficient students, and prior year mean (both school and student level); all of these average correlations are above 0.8 and most are above 0.9.

The current year average score is also strongly positively correlated with the percent of white students in the school (from 0.6-0.8 across years), whereas the correlation with MGPs is 0.2 or below in most years. Both MGPs and mean scale scores are nearly uncorrelated with the percent of female students at a school. The mean scale score has a moderate to strong negative correlation with the percent of ELL students at each school (approximately -0.6 on average), percent of students with an IEP (approximately -0.4 on average), and percent of students eligible for FRL (approximately -0.8 on average). The correlations of MGPs with these same school characteristics are also negative, but are substantially lower, with average values of about -0.2 or smaller. School MGPs are most highly correlated with the percent of students eligible for FRL.

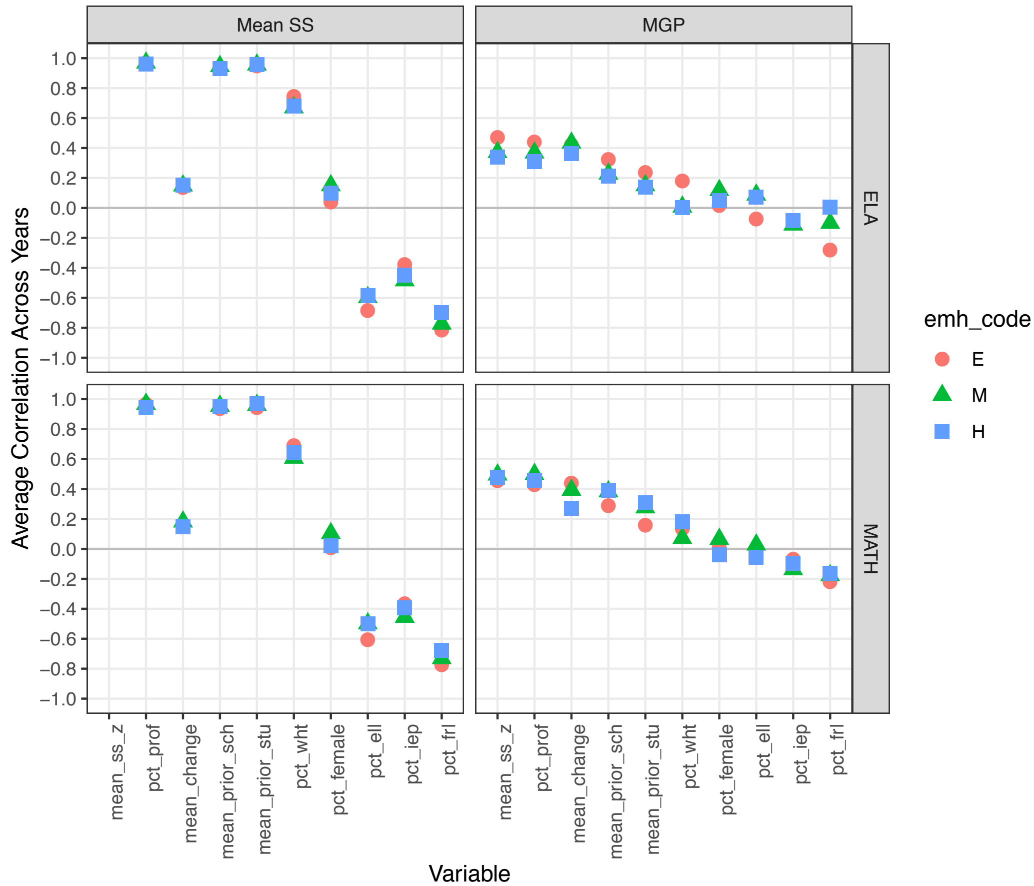

Figure 3. Average Correlations between MGP or Current Mean Scale Score and Demographic or Achievement Variables, by EMH Levels.

Figure 3 displays the same average correlations, but computed separately at each EMH unit level instead of the overall school level. In Figure 3 each panel shows average correlations (across years) between either mean scale scores or MGPs and the indicated variables for a single subject; within each panel the differently shaped and colored points represent different EMH levels. The patterns of correlations for EMH units are similar to those seen at the overall school level. The ELA MGPs appear to be slightly more correlated with some demographics at the elementary level relative to the middle and high school levels, while the opposite is true of math MGPs. The correlation between ELA MGPs and percent of FRL eligible students, for example, is approximately -0.28 at the elementary level, but only -0.1 and 0.0 on average at the middle and high school levels. This difference across EMH levels is more distinct for ELA MGPs than for math MGPs. Table 2 presents the results in Figures 2 and 3 numerically.

Table 2. Average Correlations Between MGP or Mean Scale Score and Demographic or Other Achievement Variables.

		Mean Scale Score				MGP			
Subject	**Variable**	**All**	**E**	**M**	**H**	**All**	**E**	**M**	**H**
ELA	pct_frl	-0.78	-0.81	-0.77	-0.70	-0.21	-0.28	-0.10	0.01
ELA	pct_iep	-0.42	-0.38	-0.49	-0.45	-0.12	-0.10	-0.11	-0.09
ELA	pct_ell	-0.64	-0.69	-0.60	-0.59	-0.02	-0.08	0.09	0.07
ELA	pct_female	0.08	0.04	0.15	0.10	0.05	0.02	0.12	0.05
ELA	pct_wht	0.72	0.75	0.67	0.68	0.12	0.18	0.01	0.00
ELA	mean_prior_stu	0.96	0.95	0.96	0.96	0.22	0.24	0.15	0.14
ELA	mean_prior_sch	0.94	0.94	0.95	0.93	0.29	0.32	0.23	0.21
ELA	pct_prof	0.97	0.97	0.97	0.96	0.42	0.44	0.37	0.31
ELA	mean_ss_z	--	--	--	--	0.44	0.47	0.37	0.34
ELA	mean_change	0.14	0.14	0.15	0.15	0.44	0.42	0.43	0.36
MATH	pct_frl	-0.76	-0.78	-0.73	-0.68	-0.22	-0.22	-0.18	-0.16
MATH	pct_iep	-0.39	-0.37	-0.46	-0.40	-0.11	-0.07	-0.14	-0.10
MATH	pct_ell	-0.56	-0.61	-0.50	-0.50	-0.04	-0.05	0.03	-0.06
MATH	pct_female	0.04	0.01	0.10	0.02	0.02	0.01	0.07	-0.04
MATH	pct_wht	0.67	0.69	0.61	0.65	0.14	0.13	0.07	0.18
MATH	mean_prior_stu	0.95	0.94	0.96	0.97	0.22	0.16	0.28	0.31
MATH	mean_prior_sch	0.95	0.94	0.95	0.95	0.33	0.29	0.38	0.39
MATH	pct_prof	0.85	0.97	0.97	0.94	0.40	0.43	0.50	0.46
MATH	mean_change	0.16	0.16	0.18	0.15	0.43	0.44	0.39	0.27
MATH	mean_ss_z	--	--	--	--	0.47	0.46	0.50	0.48

These results support the assertion that MGPs are not highly correlated with aggregate student demographics or prior student achievement at the school or EMH level, and are much less correlated with those characteristics than are average test scores. However, these results also highlight that MGPs are not completely uncorrelated with prior achievement or with student demographics. As noted above, there are various reasons that MGPs could be correlated with prior achievement or with student demographics, and it is not possible from these analyses to determine what the causes of the correlations in these data are.

Variance Explained by Demographics

Finally, to summarize the relationships between demographics and MGPs simultaneously, we estimate multiple linear regression models with select demographic variables as predictors, and either the current year MGP or current year mean scale score as the outcome. Year fixed effects are included in all models. For each outcome (MGP or mean scale scores), we estimated two models: Model 1 includes year fixed effects and demographic variables; Model 2 adds average prior student achievement (and hence 2009 drops out of this model). Demographics included are: percent of students designated as ELL, percent of students who are eligible for FRL, and percent of students identified as White. The two models are:

Model 1: $y_{it} = \beta_1(ELL_{it}) + \beta_2(FRL_{it}) + \beta_3(White_{it}) + \delta_t + e_{it}$

Model 2: $y_{it} = \beta_1(ELL_{it}) + \beta_2(FRL_{it}) + \beta_3(White_{it}) + \beta_4(Mean_{t-1}) + \delta_t + e_i$

Where y_{it} is either the average achievement or MGP for school or EMH unit *i* in year *t*, δ_t are year fixed effects, ELL_{it} is the percent of students identified as ELL, FRL_{it} is the percent of students eligible for FRL, $White_{it}$ is the percent of students who are identified as White, and $Mean_{t-1}$ is the average achievement in unit i in the prior year. Table 3 reports the R^2 from each of these regression models, as an indication of the extent to which we can predict average achievement or MGPs based on school demographic characteristics and prior average test scores.

Table 3. R-Squared Values for MGPs and Mean Scale Scores, by Subject and EMH Level.

		MGP		Mean Scale Score		Sample Size	
Subject	**EMH**	**Mod1**	**Mod2**	**Mod1**	**Mod2**	**Mod1**	**Mod2**
ELA	All	0.076	0.135	0.639	0.896	12198	10468
ELA	E	0.104	0.158	0.681	0.888	7918	6846
ELA	M	0.051	0.126	0.601	0.900	3885	3315
ELA	H	0.019	0.107	0.542	0.875	1980	1622
MATH	All	0.073	0.137	0.578	0.903	12207	10475
MATH	E	0.070	0.113	0.607	0.885	7921	6850
MATH	M	0.077	0.200	0.539	0.915	3889	3318
MATH	H	0.064	0.184	0.502	0.909	1981	1622

Each column of Table 3 reports R^2 for either MGPs or average scale scores (Mean SS); the "Mod1" columns include only the demographics and year fixed effects, while the "Mod2" columns also include average prior year scale scores. Across school levels and subjects, the demographic variables explain approximately 2-10% of the variation in MGPs, whereas they explain approximately 50-70% of the variation in average test scores. When adding school mean prior year scale scores, the models still explain relatively little variation in MGPs (at most 20%, for middle school math), but explain approximately 90% of the variation in average scale scores. These models support the conclusion above, that prior year achievement and student demographics are highly associated with current year average scale scores, but explain relatively little of the overall variation in school MGPs.

Stability Analyses

To investigate whether MGPs capture signal that is consistent across years, we next analyze the correlations between MGPs across years. The correlation matrices in Table 4 show the correlations between overall school-level MGPs across years, separately by subject. As described above, there are multiple factors that can cause school MGPs to vary within and between schools. As expected, correlations are highest for adjacent years (the shaded cells), and decrease (slowly) beyond that. Correlations across adjacent years are larger for math (ranging from 0.45 to 0.56) than for ELA (from 0.36 to 0.47). Note that because no 2015 data are included, the correlation between 2014 and 2016 represents the correlation between MGPs computed two years apart. The correlations between 2016 and 2017 MGPs are the smallest adjacent-year correlations in both subjects (0.45 in Math and 0.36 in ELA).

Table 4. Correlations of MGPs Across Years, Overall School Level.

ELA		**mgp_09**	**mgp_10**	**mgp_11**	**mgp_12**	**mgp_13**	**mgp_14**	**mgp_16**	**mgp_17**
	mgp_09	1.00							
	mgp_10	0.44	1.00						
	mgp_11	0.41	0.47	1.00					
	mgp_12	0.36	0.42	0.42	1.00				
	mgp_13	0.32	0.36	0.42	0.47	1.00			
	mgp_14	0.30	0.33	0.39	0.38	0.48	1.00		
	mgp_16	0.16	0.17	0.22	0.18	0.26	0.25	1.00	
	mgp_17	0.20	0.25	0.25	0.23	0.25	0.30	0.36	1.00
MATH		**mgp_09**	**mgp_10**	**mgp_11**	**mgp_12**	**mgp_13**	**mgp_14**	**mgp_16**	**mgp_17**
	mgp_09	1.00							
	mgp_10	0.55	1.00						
	mgp_11	0.43	0.53	1.00					
	mgp_12	0.38	0.42	0.51	1.00				
	mgp_13	0.33	0.39	0.44	0.56	1.00			
	mgp_14	0.31	0.33	0.33	0.42	0.53	1.00		
	mgp_16	0.19	0.21	0.21	0.23	0.26	0.33	1.00	
	mgp_17	0.22	0.20	0.18	0.18	0.20	0.32	0.45	1.00

Note: Shaded gray boxes represent adjacent-year correlations.

Table 5 summarizes the average correlations between adjacent years for MGPs and mean scale scores by EMH levels and subject, separately for 2009-2014 and 2016-17. Table 5 also shows the average adjacent-year correlations of mean scale scores, which are much more highly correlated from one year to the next (an average of 0.90 or greater in both subjects at all levels) than are MGPs (averages of 0.44 to 0.63 in the earlier years, and correlations of 0.34 to 0.57 in the more recent years, depending upon subject and EMH level). The correlations across years tend to be slightly higher in Math than in ELA for both mean scale scores and MGPs. The year to year correlations of the MGPs are similar to the values reported in prior studies, and the correlations from 2009-2014 are slightly higher in math than those reported in previous studies. The correlations between 2016 and 2017 MGPs appear slightly lower than average year to year correlations in earlier data, particularly for ELA.

Table 5. Average Adjacent Year MGP and Average Test Score Correlations, by Subject, Time Period, and EMH Level.

		2009-2014		2016-2017	
Subject	**EMH**	**Mean SS**	**MGP**	**Mean SS**	**MGP**
ELA	All	0.95	0.46	0.93	0.36
ELA	E	0.95	0.46	0.93	0.38
ELA	M	0.96	0.53	0.92	0.34
ELA	H	0.93	0.44	--	--
MATH	All	0.95	0.54	0.95	0.45
MATH	E	0.94	0.49	0.94	0.44
MATH	M	0.96	0.63	0.96	0.57
MATH	H	0.95	0.61	--	--

Note: EMH=elementary/middle/high school designation; Mean SS=average achievement.

Figure 4 plots 2016 and 2017 MGPs at the overall school level, separately by subject. Although there is a positive association between MGPs in 2016 and 2017, there is substantial variability in the 2017 MGPs for schools that had similar MGPs in 2016. The plots include dashed horizontal and vertical lines at 35, 50, and 65, which are the cutoffs used to assign SPF accountability points based on overall MGPs and subgroup MGPs. These lines illustrate that the majority of schools earn MGPs within the 35-65 range in both years, and it is relatively uncommon for a school to earn an MGP below 35 in one year and above 65 in the next year (or vice versa).

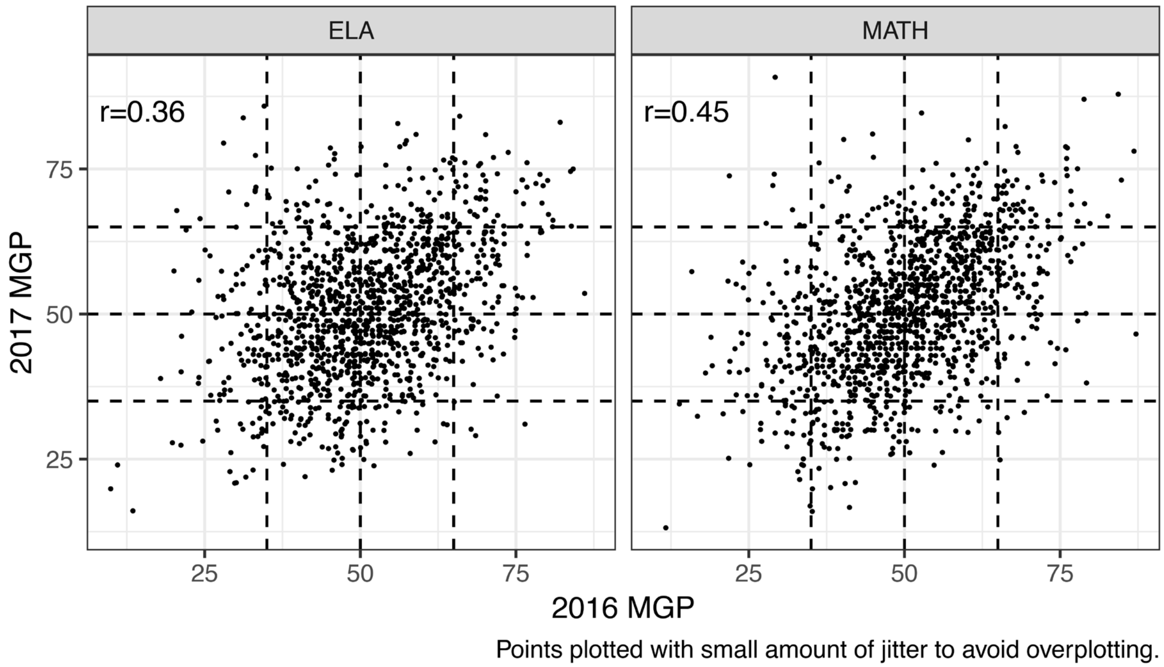

Figure 4. Scatterplot of 2016 vs. 2017 MGPs, All School Level, by Subject.

Discussion

The results presented in this report confirm some claims made about the association between MGPs and demographics (relative to average scores) and are generally consistent with claims about variability of MGPs over time. The results also raise some questions for further consideration.

Distribution of MGPs

MGPs tend to be symmetrically and approximately normally distributed across years, subjects, and EMH levels. From 2009-2014, the variability of MGPs across schools was generally larger in Math than in ELA at all EMH levels. In 2016 and 2017, however, the variability of MGPs in ELA increased while it remained constant for Math. It seems unlikely that the actual variability in effectiveness of ELA instruction increased noticeably across schools from 2014 to 2016 and more likely that this reflects a shift in what ELA MGPs represent. This does not necessarily undermine the validity of school MGPs as descriptive measures of student learning. For example, it is possible that the tests use to estimate MGPs in 2016 and 2017 better reflect the content students are intended to be learning relative to the tests used in 2014 and earlier, and that there is greater variability in effectiveness at teaching the topics covered by 2016 and 2017 tests that were not covered by earlier tests. Summary statistics of the distributions also highlight that only a relatively small portion of schools will have MGPs that earn them either “not meeting” or “exceeding” ratings for academic growth. The cutoffs used to make these ratings are near the 10th and 90th percentile of Math MGPs across years and EMH levels, while they were beyond those percentiles in ELA and are near those percentiles for the most recent years. This suggests that we can expect approximately 80% of schools to earn either “approaches” or “meets” growth standards in any given year (based on the overall student MGP). This suggests that using thresholds of 35 and 65 to assign the highest and lowest growth ratings is reasonable, in that only schools with the most extreme high/low growth ratings will be above or below these thresholds. Moving forward, developing a better understanding of the causes of the change in ELA MGP variability will be important.

Correlations of MGPs with Demographics

As expected, the MGPs were consistently less highly correlated with prior student achievement and with school demographics. In addition, whereas school demographics and average prior achievement can explain upwards of 90% of the variability in average test scores across schools, these characteristics can explain only about 20% or less of the variability in school MGPs. These results support the assertion of the TAP that the MGP growth measures are less highly associated with school demographics. To contextualize the magnitude of these associations, consider that given the standard deviation of school MGPs of approximately 12 MGP points, if we attempt to predict a school’s MGP with no additional information, we would expect our prediction to be off by about 12 SGP points. If we use prior year average test scores and select demographic variables (percent FRL, percent ELL, and percent white), we would expect our new prediction to be off by as little as 11.4 points on average, assuming that these variables explain 20% of the variation in MGPs. This is not a substantial reduction in prediction error. However, if the association between demographics and prior test scores were as strong for MGPs as it was for average test scores (explaining 80% of the variation), we would expect the prediction error to be reduced to approximately 4.6 SGP points, a substantial reduction in prediction error.

The correlation between average test scores and the percent of students eligible for FRL, for example, is approximately -0.75 across subjects and EMH levels. This is a substantial correlation, suggesting that knowing the percent of students eligible for FRL at a school can predict over half of the variability in average test scores across schools. In contrast, the correlation between percent of students eligible for free or reduced-price lunch and MGPs is closer to -0.2 on average. This suggests that knowing the percent of students eligible for free or reduced-price lunch at a school can explain only about 5% of the variability in school MGP values. Similar patterns were found for the percent of students with an IEP, percent of students who are identified as white, and the percent of students classified as English language learners. In all cases, the association with average test scores was much stronger than the association with MGPs.

School MGPs were most highly correlated with average test scores and with the change in average test scores from the prior to current year, although these correlations were moderate, ranging from approximately 0.35 to 0.45. These patterns make intuitive sense - a school whose average test scores increased from the prior to current year, or whose test scores were particularly high in the current year, are likely to be the same schools where students made the most progress on tested content. Moreover, given the moderate magnitude of the associations, it appears that MGPs and average test scores are measuring distinct aspects of student performance.

Finally, school MGPs were substantially less correlated with prior achievement, both at the student and school level. The correlation between school MGPs and prior year average test scores was approximately 0.2 to 0.4 (depending on EMH level and subject), while the correlation between current year average test scores and prior year average test scores was greater than 0.9 in all subjects and EMH levels. Again, this shows that schools with high average test scores in one year tend to be the same schools with high average test scores in subsequent years, whereas schools with high average test scores in one year may or may not be the same schools with the highest MGPs in the following year.

The analyses also highlight, however, that MGPs are not completely unassociated with prior achievement and school demographics. If the correlations are due to actual differences in student learning across schools serving different student populations, then this may or may not be a problem for the use of MGPs. But if the correlations are caused by measurement error in the student test scores and the resulting bias of SGPs, this could be problematic. Further investigation of the extent to which measurement error in test scores contributes to these correlations would be useful.

Stability of MGPs Over Time

The year-to-year correlations of school MGPs showed that although school MGPs vary from year to year, schools with higher MGPs in one year tend to have higher than average MGPs in subsequent years. This pattern supports the rationale of the TAP that school MGPs are sensitive to changes in school practices (hence varying from year to year) but also appropriate for identifying schools that would benefit from additional support (because schools with lower MGPs in the prior year will tend to have lower MGPs in subsequent years). The magnitude of the correlations indicated that there is substantial variability in school MGPs across years, although the values were similar to those reported in prior studies. The correlations between MGPs in 2016 and 2017 were lower than in prior years. The observed correlations between MGPs across adjacent years in the most recent 2016 and 2017 test administrations were 0.44 and 0.57 for elementary and middle schools in math, and 0.38 and 0.34 for elementary and middle schools in ELA. This shows that although schools with higher (or lower) MGPs in one year will tend to have higher (or lower) MGPs the following year, this is not always true. If we assume that the standard deviation of MGPs is about 12 MGP points within years, these results suggest that for two schools with the same MGP in the current year we would expect their MGP next year to differ by about 10.4 and 11 MGP points in math and ELA, respectively, rather than by 12 MGP points. It would be worth investigating whether this remains true, or whether these correlations increase as schools and teachers become more familiar with the new tests and content standards introduced during this period. Identifying factors that can explain the year-to-year variability of a school's MGP would also be useful.

Conclusion

The results were generally consistent with claims made about school MGPs regarding the associations between MGPs and demographics and the stability of MGPs across years. However, the results also raise some additional questions regarding: the change in the distribution of ELA MGPs, the small but non-zero association between MGPs and demographics or prior achievement, and potential factors that could explain the variability of MGPs both between and within schools. Finally, we note that, while relevant to evaluating the uses and interpretations of MGPs in the SPF system, these results do not constitute a complete evaluation or validity argument to support the use of MGPs as a school accountability metric.

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Appendix

Descriptive Statistics for Constant Sample

		All School Level			Elementary School			Middle School			High School		
Subject	**Year**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
ELA	9	51.0	9.1	1153	50.7	9.8	870	50.5	9.0	355	51.4	9.5	278
ELA	10	50.5	9.6	1153	50.5	10.2	870	50.1	9.2	355	51.8	9.1	278
ELA	11	51.3	9.0	1153	51.1	9.5	870	51.4	9.4	355	51.5	10.0	278
ELA	12	50.9	8.9	1153	50.8	9.6	870	50.7	8.6	355	52.2	9.5	278
ELA	13	50.7	8.9	1153	50.6	9.7	870	50.7	8.0	355	51.1	9.5	278
ELA	14	50.7	9.0	1153	50.5	9.7	870	50.7	8.4	355	51.5	8.5	278
ELA	16	51.0	11.7	1153	51.2	11.8	870	50.8	12.2	355	--	--	--
ELA	17	51.0	11.8	1153	51.2	11.7	870	50.6	12.7	355	--	--	--
MATH	9	50.8	11.8	1153	51.0	12.3	872	50.1	12.8	356	50.6	11.1	277
MATH	10	50.8	12.4	1153	50.8	12.9	872	50.9	12.6	356	52.8	10.5	277
MATH	11	51.0	11.3	1153	50.7	11.8	872	51.5	11.7	356	52.6	10.3	277
MATH	12	51.1	11.6	1153	51.1	12.1	872	51.1	12.3	356	51.9	10.7	277
MATH	13	50.8	11.2	1153	50.8	11.9	872	50.3	11.8	356	51.1	10.4	277
MATH	14	50.7	11.4	1153	50.6	11.9	872	50.7	11.5	356	52.5	10.5	277
MATH	16	50.7	11.9	1153	50.6	12.7	872	51.1	10.8	356	--	--	--
MATH	17	50.9	11.8	1153	51.1	12.4	872	51.0	11.3	356	--	--	--

This table shows summary statistics for MGPs using only schools that appear in all 8 years of data for the All, E, and M levels, or all 6 years of data for the H level.

Descriptive Statistics for Demographics

			Mean Scale Score		Percent White		Percent FRL		Percent ELL		Percent IEP		Percent Female	
EMH	**Subject**	**N**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
All	ELA	12198	-0.04	0.42	0.57	0.27	0.45	0.28	0.18	0.21	0.10	0.06	0.49	0.05
E	ELA	7918	-0.02	0.43	0.56	0.28	0.46	0.29	0.19	0.22	0.11	0.05	0.49	0.05
M	ELA	3885	-0.04	0.43	0.57	0.28	0.44	0.27	0.18	0.21	0.10	0.06	0.49	0.06
H	ELA	1980	-0.05	0.41	0.62	0.27	0.39	0.24	0.15	0.19	0.09	0.07	0.49	0.06
All	MATH	12207	-0.05	0.44	0.57	0.27	0.45	0.28	0.18	0.21	0.10	0.06	0.49	0.05
E	MATH	7921	-0.04	0.45	0.56	0.28	0.46	0.29	0.19	0.22	0.11	0.05	0.49	0.05
M	MATH	3889	-0.08	0.45	0.57	0.28	0.44	0.27	0.18	0.21	0.10	0.06	0.49	0.06
H	MATH	1981	-0.09	0.45	0.62	0.27	0.39	0.24	0.15	0.19	0.09	0.07	0.49	0.06

Note: M=mean; SD=standard deviation.