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THE LONG-TERM EFFECTS OF GRADE INFLATION

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ABSTRACT

Average grades continue to rise in the United States, raising the question of how grade inflation impacts students. We provide comprehensive evidence on how teacher grading practices affect students' long-run success. Using administrative high school data from Los Angeles and from Maryland that is linked to postsecondary and earnings records, we develop and validate two teacher-level measures of grade inflation: one measuring average grade inflation and another measuring a teacher's propensity to give a passing grade. These measures of grade inflation are distinct from teacher value-added, with grade inflating teachers having moderately lower cognitive value-added and slightly higher noncognitive value-added. These two measures also differentially impact students' long-term outcomes. Being assigned a higher average grade inflating teacher reduces a student's future test scores, the likelihood of graduating from high school, college enrollment, and ultimately earnings. In contrast, passing grade inflation reduces the likelihood of being held back and increases high school graduation, with limited long-run effects. The cumulative impact is economically significant: a teacher with one standard deviation higher average grade inflation reduces the present discounted value of lifetime earnings of their students by $213,872 per year.

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1 Introduction

Average grades have risen substantially in recent years (Gershenson, 2018) with high school grades having increased by nearly half a letter grade in the past 40 years (see Figure 1).[1] Although this increase might, in principle, reflect real improvements in student learning, standardized test scores have not increased at the same rate (Sanchez and Moore, 2022). This divergence suggests that the rise in average grades may reflect a shift toward lower grading standards and an increase in grade inflation.[2] Understanding how grade inflation impacts students – both in their academic performance and in their subsequent educational and professional outcomes – constitutes a central question for researchers and policymakers. Indeed, school districts throughout the country are in the throes of contentious debates about whether and how to change grading standards, with many teachers reporting an increase in practices that lower grading standards and raise grade inflation (Alex, 2022; Randazzo, 2023; Graham, 2017; Las Vegas Review-Journal Editorial, 2023; Griffith and Tyner, 2025).

Grade inflation can arise from a variety of sources, but teachers interact most closely with students and generally have discretion over assigning grades. Effective teachers benefit students across numerous dimensions in both the short- and long-run, including test scores, suspensions, absences, effort, and earnings in adulthood (Rivkin et al., 2005; Koedel and Rockoff, 2015; Petek and Pope, 2023; Jackson, 2018; Chetty et al., 2014a,b). However, the practices that make some teachers more effective than others are poorly understood, which prevents school leaders and policymakers from making optimal personnel, training, and policy decisions (Staiger and Rockoff, 2010). As a notable exception to this critique, a small literature shows that teachers' grading practices, biases, and expectations affect student outcomes (Figlio and Lucas, 2004; Carlana, 2019; Gershenson et al., 2022; Papageorge et al., 2020). Those findings suggest that teachers, schools, and districts could actively change or adopt specific grading policies to benefit students. This paper focuses on teachers' individual grading practices. We use administrative data from a large school district and a state to characterize several measures of teacher grade inflation and to study the

[1] Figure 1 shows that average high school GPAs have risen by 0.48 GPA points since the mid 1980s. Similarly, average college GPAs have risen by 0.35 GPA points.

[2] Much of the prior literature has referred to this concept as "lower grading standards." We use the terms grade inflation, grading leniency, and reduced grading standards interchangeably. We do not take a stance on the correct name for this phenomenon.

effects of these grading standards on high school students' short- and long-run educational and labor market outcomes.

Debates over grading policies hinge on the theoretical ambiguity about whether high standards boost performance by eliciting effort from students or hamper performance by discouraging students. One camp suggests that grade inflation is harmful to students, leaving them unprepared for future educational or vocational endeavors and decreasing their overall effort (Wright, 2019). Others suggest that grade inflation does not negatively affect students and that high grading standards might even discourage students (Kohn, 2002). The arguments put forth by these two camps are not necessarily mutually exclusive. Minimum grades are required to pass classes and continue in high school, so grade inflation may help students by allowing them to continue to accumulate human capital and to graduate when they otherwise would drop out. However, high standards for awarding higher grades may provide an incentive for students to study and learn the material. If this incentive is reduced, students may study less and learn less. These two effects are in tension: inflated grades can reduce early failure and dropping out, but blunt incentives to study and learn material.[3] This is a key insight in theoretical models of grade inflation; changing the standards for graduation may increase effort and learning for some students, while reducing effort and learning for others (Costrell, 1994; Betts, 1998).[4] For example, for students on the margin of failing a class, grade inflation may be pivotal for receiving credit required for graduation. However, students who are not at risk of failing may be harmed by the reduced incentive to study. Given the theoretical ambiguity and clear policy importance, empirical evidence can help settle the question of which grading practices are best for students.

In this paper, we study the effects of grade inflation on high school students. While both Costrell (1994) and Betts (1998) focus on a single standard (passing), in reality, there are many standards that teachers set, such as the standard for earning an A or a B. Hence, we separate grading standards into two categories, one capturing general leniency and the other capturing a particularly policy-relevant margin of grading, the probability of receiving a passing grade. The general leniency measure captures the incentive that grades represent for students to learn more

[3] Landaud et al. (2024) show that randomly higher GPAs have long-term benefits for students. This is likely one source of the incentive effects of grades.

[4] Costrell (1994) nicely illustrates this key tension but makes simplifying assumptions such as a single credential and a pooling equilibrium for wages for all students with the same credential level.

because a higher grade conveys better signals to future employers or universities. As noted by Costrell (1994); Betts (1998), the direction of the effect of general grade inflation is theoretically ambiguous, therefore this measure captures an average effect across students. The second captures the policy implications of a failing grade: students who fail a class must retake it to earn credit; if they fail to earn credit in key classes, they do not receive a diploma.[5]

To operationalize these categories, we construct two teacher-specific measures of grade inflation. The first is "mean grade inflation," which measures how much higher *on average* grades are than expected, conditional on student standardized test scores and other characteristics. While our measures share some similarities to measures developed by Figlio and Lucas (2004) and Gershenson et al. (2022), our measure is meaningfully distinct empirically.[6] The second is a novel measure, "passing grade inflation," which measures inflation at the margin of passing a class – that is, inflating the student's grade from an F to a D or higher. Again, we focus on the passing margin because it has particular policy relevance – students do not receive credit for the class if they do not pass. We find that these two measures of grading standards are correlated, but distinct, concepts. Consistent with the literature, mean grade inflation decreases test scores in the next year; we contribute new evidence that mean grade inflation also has long-term negative effects on students' high school, postsecondary education, and labor market outcomes. In contrast, we find that lower passing grading standards may help students on the margin of passing: passing grade inflation increases five-year high school graduation and enrollment in certain postsecondary education following high school.

To construct our measures of grade inflation, we use administrative data on high school students in two distinct settings. We observe students and teachers from the nation's second-largest school district, the Los Angeles Unified School District (LAUSD), and from the universe of public high schools in Maryland. We also link the Maryland high school data to administrative college and earnings records. These data offer complementary strengths. More frequent testing in the LAUSD allows us to estimate the impacts of grading standards on future test scores with more precision and to include high school students from higher grade levels in our analysis sample. The Maryland data allow us to examine additional longer-term outcomes, such as college enrollment,

[5]In addition to the institutional importance of passing a class, we focus on this second measure of grading standards because some schools may have specific policies that pressure teachers not to fail their students.

[6]Our measure is more similar to the measure used in Mozenter (2019).

college graduation, and earnings. Despite the different settings, the estimated effects of grade inflation on student outcomes are similar across the two settings.

Using these administrative data sets, we confirm that average high school grades are increasing over time and that these grade increases likely represent grade inflation rather than increases in human capital. Figure 2 shows that average grade point averages (GPAs) increased over the 2004 to 2013 school cohorts in the LAUSD and the 2013 to 2023 school cohorts in Maryland. In the LAUSD, the mean GPA increased from 2.25 to 2.45, roughly a quarter of a letter grade. For "average" students who scored within one-tenth of a standard deviation of the average on one of the state standardized test, the average GPA rose by 0.23; for "top" students scoring over 3 standard deviations above the mean on one of the tests, the average GPA rose by 0.34.[7] In Maryland, the trend in average GPAs is remarkably similar to that in the LAUSD. In addition, Appendix Figure A.1 shows that these increases in average GPA occur in both math and English classes. The increase we document in Maryland and the LAUSD is corroborated by the literature and national data (see Figure 1). Several studies have shown that grading has become more lenient over time, both in high school and in college (Zhang and Sanchez, 2013; Gershenson, 2018; Hurwitz and Lee, 2018; Denning et al., 2022; Sanchez and Moore, 2022).

This paper makes several contributions to our understanding of grade inflation and grading practices. The first is the conceptual contribution of distinguishing mean grade inflation, which is somewhat similar to measures constructed by others in the empirical literature, from passing grade inflation, which is novel. By making this distinction, we can explore trade-offs inherent in grading leniency along the dimensions of effort elicitation and discouragement. These two measures of grading leniency are correlated but distinct, with correlation coefficients of 0.86 in the LAUSD and 0.35 in Maryland,[8] and therefore represent related but different grading practices of teachers. Because we find empirically that mean grade inflation and passing grade inflation often have opposite effects on student outcomes, distinguishing between them is important. We also validate our measures of grading leniency in several ways. We use two tests to show that

[7]The achievement of these top students is unlikely to have increased substantially over time, suggesting that the increase in grades may reflect grade inflation rather than increases in human capital.

[8]Failing a course is uncommon in Maryland. About 97 percent of students pass their math classes and 98 percent pass their English classes. As such, there is less variation in passing grade inflation in Maryland compared to the LAUSD, so it is not surprising that the correlation between mean and passing grade inflation is lower in Maryland than in the LAUSD.

our measures are forecast unbiased. Our measures perform as well or better than cognitive value-added on these tests, and perform substantially better than existing grade inflation measures from the literature. Additionally, we find very similar results when either constructing grade inflation measures using extra demographic controls available in Maryland or constructing grade inflation measures separately for math and English courses.

Second, we explore how grade inflation relates to other teacher characteristics. One advantage of our data is that we can construct several value-added measures, including those related to student motivation and learning as in Petek and Pope (2023), as well as test score value-added. We document that grade inflation is somewhat correlated with other well-established teacher characteristics, such as cognitive value-added (correlation -0.41 in the LAUSD and -0.31 in Maryland) and noncognitive value-added (correlation 0.16 in the LAUSD and 0.12 in Maryland). If these correlations are causal, they suggest that teachers may face tradeoffs in classroom practices. However, these correlations also show that grade inflation is a distinct concept from value-added.[9]

Third, we evaluate the effects of both measures of grade inflation on student academic outcomes such as high school graduation, future test scores, and SAT test-taking. Previous work has documented that more lenient teachers reduce performance on tests in subsequent grades (Figlio and Lucas, 2004; Mozenter, 2019; Gershenson et al., 2022).[10] Consistent with prior evidence, we show that having higher mean grade inflating teachers reduces performance on future tests. Having math and English teachers who are on average one standard deviation higher in mean grade inflation reduces test scores in the next year by approximately 0.02 standard deviations. We build on previous work by documenting the persistent effects of grading leniency.[11] We find

[9] While we report correlations for measures of teacher value-added and grade inflation, conceptually they are different in important ways. Teacher value-added can be thought of as a black box, and measures the combined effect of all teacher attributes and behaviors on student success. Teacher value-added is hard to manipulate via policy, because it is less clear what contributes to high teacher value-added. In contrast, grading practices are a policy choice of teachers (or other school administrators) of how to map student performance into grades.

[10] Our paper is related to work that uses a change in grading policy in North Carolina to show that inflating grades reduces student attendance and ACT scores for some students (Bowden et al., 2023). This paper is a useful evaluation of statewide policy, but does not focus on individual teachers' roles in affecting grades. Insler et al. (2021) uses random assignment of college instructors at the US Naval Academy to show that teachers who give higher grades tend to harm performance in follow-on courses. We extend this study by focusing on high school students, considering longer-term outcomes, and developing and validating measures that can be used in settings without random assignment. Betts and Grogger (2003) consider the consequences of grade inflation at the school level and construct measures similar to Figlio and Lucas (2004) and Gershenson et al. (2022).

[11] Mozenter (2019) finds no effect on longer-term outcomes, but the author only considers the effects on one grade inflation measure that is similar to but different than our measure of mean grade inflation and focuses on middle school students.

that having a one standard deviation higher mean grade inflating teacher decreases the likelihood of graduating high school by 0.8 percentage points in the LAUSD and 0.1 percentage points in Maryland, and of taking the SAT by 0.5 percentage points in both settings.

We further contribute to the existing literature by documenting important heterogeneity in the effects of different types of grade inflation. While higher mean grade inflation is detrimental to students' future academic achievement, having a teacher with a higher passing grade inflation measure is beneficial for students on some measures. We show that having higher passing grade inflating increases the likelihood of graduating from high school. Having math and English teachers who are on average one standard deviation higher in passing grade inflation has no effect on future standardized test scores, but increases the likelihood of graduating high school by 0.2-0.5 percentage points. Additionally, having a higher passing grade inflating teacher decreases the likelihood of being held back in the next year by 1.2 percentage points in the LAUSD and 0.4 percentage points in Maryland. Hence, the nature of the grade inflation is critical for understanding its effects on student outcomes.

Fourth, we present evidence that grade inflation has longer-term impacts on students, influencing their postsecondary enrollment as well as labor market outcomes. We find that exposure to higher mean grade inflating teachers reduces enrollment in postsecondary education programs, and also reduces graduation from Associate's degree programs. Furthermore, mean grade inflation reduces the likelihood that a student will be employed and decreases their earnings up to six years after expected high school graduation. The cumulative impact of higher grade inflating teachers is economically significant. A teacher with one standard deviation higher mean grade inflation reduces the present discounted value of lifetime earnings of their students by $213,872 per year of teaching. On the other hand, passing grade inflation increases enrollment in Associate's programs, but reduces enrollment in and graduation from Bachelor's programs. We also find suggestive evidence that passing grade inflation may have a small positive effect on students' early labor market outcomes, though those results are sensitive to the definition of employment and only appear in the first few years post high school.

Fifth, we show that these two measures of grade inflation have heterogeneous effects among different groups of students, especially along the academic performance distribution. Having a higher mean grade inflating teacher has similar negative effects on students' future test scores for students of different academic performance, but reduces grade retention more among students in the bottom of the 8th grade GPA distribution. In addition, the positive effects of passing grade inflation are concentrated among lower-performing students: having a teacher who engages in passing grade inflation increases high school graduation rates more and reduces grade retention more among students in the bottom of the 8th grade GPA distribution. These results suggest that passing grade inflation are more beneficial for low-achieving students than for high-achieving students.

The paper proceeds as follows. Section 2 discusses the data and describes grades in the LAUSD and Maryland. Section 3 discusses our construction and estimation of the two different types of grading leniency. Section 4 discusses the results. Section 5 concludes.

2 Data

We study grading practices in two settings, the Los Angeles Unified School District (LAUSD) and the state of Maryland, using two datasets with complementary strengths. During the time covered in our data in the LAUSD, students took end-of-year standardized tests through 11th grade. This allows us to create measures of grade inflation and value-added, which rely on current and lagged test scores, and evaluate the impact of those measures on future test scores through 11th grade. In addition, LAUSD teachers graded their students on noncognitive dimensions (effort and cooperation) along with the traditional academic GPA, allowing us to explore how grade inflation relates to both cognitive and noncognitive measures of value-added. Finally, students in the LAUSD frequently received failing grades for classes, which means that the passing margin is meaningful for a large portion of the analysis sample. However, the LAUSD data lacks information on student demographic characteristics such as race, gender, and measures of socioeconomic status, and does not follow students beyond high school.

We augment our analysis with linked K-12, college, and employment data from Maryland, which allows us to explore longer-term outcomes in a sample that covers more recent years and contains more demographic characteristics. Because in Maryland, only approximately two years of math and English standardized exams are administered in high school,[12] our Maryland analysis

[12] Algebra I, Algebra II, Geometry, and either 9th or 10th grade English were the standardized tests that were

is based on a subset of high school students skewed toward grades 9 and 10. Furthermore, the passing grade inflation measure in Maryland has less variation than the measure in the LAUSD, as few students in Maryland fail their classes in high school.[13] We therefore view the two data sources as complements, which together tell a more complete story about the effects of grade inflation. Wherever possible, we report estimates from both the LAUSD and Maryland in order to provide additional validation of the results.

Los Angeles Unified School District Data

The LAUSD data contain student-year observations from 2004 to 2013 linked to class and teacher identifiers.[14] We focus on high school students (grades 9 to 12), using 8th grade test scores and GPAs to form certain controls and in some heterogeneity analyses. In 2004, the school district was 72.5 percent Hispanic, 11.8 percent Black, and 9.1 percent white.[15] In addition, over 70 percent of students received free and reduced price lunch in 2010.[16] Historically, the LAUSD's academic performance has been lower than the national average. Graduation rates were below 50 percent in the early 2000s but rose to 70 percent by 2014.

During this time period, students in grades 8 through 11 took annual California Standards Tests in math and English. These high-stakes, multiple-choice tests were administered to all California students each spring. We standardize test scores at the grade-year level. In addition to yearly test scores, the data include information on students' grades in each course and their overall GPA. Students are given a grade of A, B, C, D, or F for each class and GPA is measured on a 0 to 4 scale (e.g., A = 4.0, B = 3.0). These two variables, GPA and end-of-year test score, are the main components of our measures of grade inflation. The data also provide information about student behavior, which we use to construct measures of teacher value-added and as next-year outcomes. We use information about the number of days a student was suspended, the number of days a student was absent, whether a student did not progress on time to the next grade (i.e.,

administered to high school students in Maryland during our study's time period.

[13] Between 97 to 98 percent of students pass their math and English classes in Maryland, whereas only 68 to 79 percent of students pass their math and English classes in the LAUSD.

[14] The data actually begin in 2003, but our main analysis sample starts in 2004 so that we have lagged test scores and lagged behavioral measures for use as controls.

[15] These statistics were constructed using the files at https://www.cde.ca.gov/ds/ad/fileshistenr8122.asp.

[16] These statistics can be found at https://dq.cde.ca.gov/dataquest/.

held back),[17] and whether the student was an English Language Learner (ELL). In addition to next-year student behavioral outcomes, we also use next-year test scores, whether a student took the SAT, their SAT score conditional on taking it, whether a student took the PSAT, their PSAT score conditional on taking it, and indicators for graduating high school within four or five years of starting ninth grade as outcome variables in the LAUSD.

Table 1 presents student-level summary statistics for the 868,217 high school students enrolled between 2004-2013 for which we have information about test scores, grades, and behavior. In this table we average over years, so that each observation represents one student.[18] Several characteristics are notable in the LAUSD. First, measures of student success are low. Only 46 percent of ninth graders graduate from the LAUSD within 4 years and 55 percent graduate within 5 years, and more than 11 percent of students are held back at some point. The average student is absent for 7 percent of school days. While the LA data provide very few demographic characteristics, 18 percent of students are English language learners. In the LAUSD, our best measure of college intention is the SAT, which is taken by 38 percent of students in our data. Among those who take the SAT, the average score is 1334 on a 2400 scale, which is approximately the 30th percentile of test takers. Grades are low, with an average GPA of 2.33. Subject-specific GPAs are even lower for math and English, with averages of 1.79 and 2.22, respectively. Students' average noncognitive grades are similar to average academic GPAs, with an average effort GPA of 2.18 and an average cooperation GPA of 2.33.

Maryland Data

The Maryland data contain student-year observations from 2013 to 2023. They are provided by the Maryland Longitudinal Data System[19] and include educational records from the Maryland State Department of Education linked to Maryland Higher Education Commission records and Maryland Department of Labor records. As with the LAUSD data, we focus on high school stu-

[17] A student is counted as held back in a particular year if their administrative grade level is the same as their administrative grade level in the previous year

[18] We require that students have the following information to be included in this sample: school, grade level, year, math or English grade inflation measures, math or English test score value-added measures, noncognitive teacher value-added measures (GPA value-added, fraction days absent value-added, suspension value-added, and held back value-added), lagged math and English test scores, lagged total GPA, lagged fraction days absent, lagged indicators for suspension and held back status, an indicator for current ELL status, current English GPA, and current fraction days absent. This is the same restriction we make in our empirical analysis.

[19] See https://mldscenter.maryland.gov/.

dents (grades 9 to 12), using 8th grade test scores and GPAs to form certain controls and in some heterogeneity analyses. For high school students, we observe end-of-year test scores in Algebra, Geometry, and one or both of 9th and 10th grade English,[20] as well as course grades, demographic characteristics, and teacher identifiers.[21] Notably, the Maryland data contain information about gender, race, ethnicity, and a proxy for low family income (Free and Reduced Price Meals), which the LAUSD data does not provide. We construct test scores and grades in a similar fashion to those in the LAUSD sample. We standardize test scores at the grade-year level, and grades in each course are measured on a 0 to 4 scale.

Most of the higher education records are sourced from the National Student Clearinghouse, which allows us to track students' enrollment and degrees achieved at any school in the United States, with additional information for those students who stay in Maryland. Our main higher education outcomes of interest are enrollment in any higher education institution one and two years after high school and graduation from any higher education institution four and six years after high school. We are also able to explore enrollment and graduation separately for different degree types as defined by the Maryland Higher Education Commission; we focus on Associate's and Bachelor's degrees.

The workforce records from the Department of Labor, which provide quarterly earnings records, are based on unemployment insurance. They are therefore subject to the usual caveat that we are only able to see employment with employers who have mandatory reporting to the state unemployment insurance system; self-employment, for example, is not captured in our data. Our main workforce outcomes of interest are employment and annual earnings one and six years after high school. Our main measure of employment is an indicator for having nonzero earnings in any quarter of the year.[22] Our main measure of earnings is winsorized at the 99th percentile. For both higher education and workforce outcomes, we define the time relative to their expected high school graduation – that is, four years after the student was first observed in 9th grade – to avoid basing

[20] The grade in which the English test was offered changed during our sample period.

[21] In addition to only administering end-of-year standardized tests for a subset of courses, Maryland's exams also changed several times throughout the sample period. Originally, the standardized tests were the High School Assessments (HSA), which switched to the Partnership for the Assessment of Readiness for College and Careers (PARCC) in 2014, which then switched to the Maryland Comprehensive Assessment Program (MCAP) in 2022. The switch to the MCAP was originally intended for the 2019-2020 school year but was delayed by the pandemic.

[22] We also explore a more restrictive definition that requires earnings in two quarters or more (e.g., more than a summer job), which yields qualitatively similar results.

the timing on a potentially endogenous outcome such as high school graduation. For example, "enrollment one year after high school" is measured as whether the student was enrolled in a higher education institution five years after 9$^{\text{th}}$ grade.

Table 2 presents summary statistics for the Maryland sample of high school students enrolled between 2013 to 2023 for which we have information about test scores, grades, and behavior.[23] As for the LAUSD, in this table we average over years so that each observation represents one student. The average math and English test scores are skewed slightly positive, consistent with a small positive selection into the sample given that we require students to have lagged values of test scores and course grades. The average GPA is 2.47 in math and 2.67 in English and 69 percent of students take the SAT. Graduation rates are slightly higher than national averages with 92 percent of 9$^{\text{th}}$ graders graduating within 5 years. Thus, the students in Maryland appear to have better educational outcomes than those in the LAUSD, where many fewer students took the SAT and graduated within 5 years. The Maryland sample is 42 percent white, 36 percent Black, 12 percent Hispanic, and 7 percent Asian. For longer-term outcomes, 67 percent of students are enrolled in any postsecondary education a year after high school and 27 percent graduate within 4 years. Lastly, 63 percent of students are employed in a job covered by unemployment insurance six years after their expected high school graduation.[24]

3 Estimation

In this section, we describe the construction and validation of two measures of teacher-specific grade inflation, mean and passing grade inflation. We also describe the construction of standard measures of teacher value-added and the process by which we estimate measurement-error-corrected correlations between our various teacher-level measures. Finally, we describe how we estimate the effects of grade inflation on student outcomes.

[23] We make the same sample restrictions in Maryland as in the LAUSD: we require that students have school, grade level, year, math or English grade inflation measures, math or English test score value-added measures, noncognitive teacher value-added measures (GPA value-added, fraction days absent value-added, suspension value-added, and held back value-added), lagged math and English test scores, lagged total GPA, lagged fraction days absent, lagged indicators for suspension and held back status, an indicator for current ELL status, current English GPA, and current fraction days absent.

[24] This is slightly lower than for public high school graduates in Texas during the early 2000s, who have an observed employment rate of 76 percent 9 to 11 years after high school graduation Black et al. (2023).

3.1 Constructing Measures of Teacher Grade Inflation

In practice, teachers have a large amount of discretion over how they assign grades. For a group of students with the same underlying performance, different teachers could map that performance onto different grades. Variation in the mapping of performance to grades can change, for example, the number of students who receive a grade of A, the average GPA of a class, or the number of students who fail. Exposure to teachers who apply different mappings of performance to grades is likely to have different effects on students. For instance, a teacher who passes most students might reduce the likelihood that a student repeats a grade or is unable to graduate due to not passing a required class. Alternatively, a teacher who gives many students A grades might reduce the incentive for top students to study, which could hurt their performance in future classes by lowering their learning or motivation. From these two examples, it is clear that grade inflation theoretically could aid or damage a student's future academic performance. Whether grade inflation helps or hurts depends critically on both the type of grade inflation in which the teacher engages and the characteristics of the student.

With this motivation in mind, we define measures for two types of grade inflation. First, we are interested in characterizing "mean grade inflation," which measures how much the assigned grade is inflated on average. Second, we are interested in characterizing "passing grade inflation," which measures how likely a teacher is to pass a student (i.e., assign the student a D or higher instead of an F).

To construct our first measure, mean grade inflation, we model student i's grade $Grade_{ijst}$ assigned by teacher j at school s during year t in a focal subject, math or English, as

$$\begin{aligned} Grade_{ijst} &= \beta_1 TestScore_{ijst} + \beta_2 Grade_{ist-1} + \beta_3 MathTest_{ijst-1} \\ &\quad + \beta_4 EnglishTest_{ijst-1} + GI^{mean}_{jt} + X_{ist}\beta + \varepsilon_{ijst}. \end{aligned} \tag{1}$$

The object of interest is GI^{mean}_{jt} which is the year-specific teacher fixed effect.[25] This is the teacher's average contribution to grades after controlling for several important factors.[26] First, we account for

[25] Our method bears some resemblance to methods in Figlio and Lucas (2004), Gershenson et al. (2022), and Mozenter (2019). We discuss differences between these methods and ours in section 3.3.

[26] In our analysis sample, we exclude student-year observations with more than one teacher or course in the focal subject.

a student's contemporaneous performance in the focal subject as measured by the corresponding subject test score, $TestScore_{ijst}$. Second, we control for the student's grade in the focal subject from the prior year, $Grade_{ijst-1}$. Third, we control for prior test scores in both math and English as well as a vector of other student characteristics (X_{ist}), including school, grade, and year fixed effects, an indicator for ELL status, previous year total academic GPA, previous year fraction of days absent, previous year suspension, and previous year held back status.[27] As is common in the teacher characteristics literature, we estimate each subject separately in some cases.

For each teacher, we calculate mean grade inflation, $\widehat{GI}_{jt}^{mean}$, which represents how much a teacher raises (or lowers) their students' grades on average relative to their academic performance. Our second measure of grade inflation replaces $Grade_{ijst}$ in Equation 1 with an indicator for student i passing teacher j's class at school s during year t, where passing is defined as receiving a grade of D or better. The object of interest is again the year-specific teacher fixed effect, denoted as GI_{jt}^{pass}, in the modified Equation 1. For each teacher, we calculate passing grade inflation, $\widehat{GI}_{jt}^{pass}$. As discussed, we create this second measure to capture different grading standards that teachers might have. Some teachers might raise the grades of their students in general, whereas others might specifically raise grades only when students are on the margin of failing the class. Theory suggests that these two measures of grading leniency may have different effects on students' future academic performance.

We make several adjustments to our measures when we use them to estimate the effects of grade inflation on future outcomes. Following Chetty et al. (2014a), we estimate $\widehat{GI}_{jt}^{mean}$ and $\widehat{GI}_{jt}^{pass}$ using a jackknife empirical Bayes estimator. This approach uses data from surrounding years to estimate a teacher's propensity to grade inflate in year t, which avoids biasing estimates of the effects of teacher grade inflation on student outcomes (Jacob et al., 2010). Including year t in the prediction would likely bias the estimates because unobservable characteristics in year t that are related to any dimension of student performance would be captured in both the measure of grade inflation in year t and the outcome of interest.

The estimates $\widehat{GI}_{jt}^{mean}$ and $\widehat{GI}_{jt}^{pass}$ are fundamentally defined as residuals. It is worth considering what these estimates could be capturing aside from grade inflation. We rule out some

[27] For the Maryland sample, because students do not necessarily take math and English exams every year, we replace the previous year test scores with the most recent previous test scores.

potential alternative explanations by controlling for student characteristics. For example, student performance is accounted for in multiple ways; Equation 1 includes the student's contemporaneous and past standardized test score and past grades. This accounts for students who might perform poorly on standardized tests, but demonstrate their understanding of the subject through their performance on non-test assessments.

However, $\widehat{GI}_{jt}^{mean}$ could represent other techniques a teacher uses to improve their students' grades in a way not captured by contemporaneous test scores. Such a technique could be a skill the teacher conveys to their students that improves grades but not test scores, such as helping students learn to work in groups. In our setting, a teacher who is very good at conveying skills not captured by contemporaneous test scores would have a high $\widehat{GI}_{jt}^{mean}$ measure. Alternatively, a teacher might consistently be assigned better students and thus have classrooms with higher peer effects. In both cases, we would expect higher $\widehat{GI}_{jt}^{mean}$ to *improve* future performance in the next year, through new skills or through better peers. However, our results will show that high $\widehat{GI}_{jt}^{mean}$ teachers reduce future performance, which supports our interpretation of this residual as a measure of grade inflation.

The ultimate goal in creating our measures is to capture how much grade inflation a student experiences in a given year across their math and English teachers. To accomplish this, we construct the estimates $\widehat{GI}_{jt}^{mean}$ and $\widehat{GI}_{jt}^{pass}$ for each teacher-year, separately by subject, and standardize them to be mean zero, standard deviation one within year and subject.[28] We then create a combined measure of the math and English grade inflation a student experiences in a year by summing the standardized grade inflation measures across subjects and standardizing the resulting sum so that it is mean zero, standard deviation one within each year. We use this approach to create measures of both mean and passing grade inflation that are combined across subjects. Our main analysis of the effects of grade inflation on student outcomes, detailed further in Section 3.5, uses these subject-combined versions of mean and grade inflation.[29]

[28]Calculating at the subject, rather than course, level means that if a teacher teaches two different math classes in a year, our measure of grade inflation for that teacher will be the same for those two classes.

[29]For robustness, we also estimate the effects of grade inflation on student outcomes using the pre-summation, subject-specific grade inflation measures, and find very similar results.

3.2 Validating Measures of Teacher Grade Inflation

Our measures of grade inflation face some of the same challenges faced by measures of teacher value-added. First, these measures are estimated with noise and may not be predictive of actual student outcomes out of sample, leading to estimation error. For example, if student grades are very noisy year after year due to random variation in unobservable factors, that variation could drown out the teacher signal, and teacher measures would not be very predictive of student outcomes. Second, these measures may be biased due to student selection on factors omitted in our econometric model. Both of these concerns would result in forecast-biased measures of grade inflation. Following Chetty et al. (2014a), forecast bias can be written as a function of the correlation between the true theoretical teacher measure and the estimated teacher measure:

$$Bias = 1 - \frac{cov(GI_{jt}, \widehat{GI}_{jt})}{var(\widehat{GI}_{jt})}.$$

Estimation error and selection both lead to forecast bias. With estimation error, very noisy estimates of grade inflation reduce the correlation on the right hand side of the expression. With selection, the estimated grade inflation measure could also include the effect of omitted variables on grades (or passing), therefore reducing the covariance between the true and estimated measures relative to the variance of the estimated measure. In both cases, the lower correlation or covariance increases the bias. To determine whether estimation error or selection pose concerns for our grade inflation measures, we conduct two tests for forecast bias.[30]

The first test addresses estimation error by checking whether teacher grade inflation measures are predictive of student grades out of sample. To implement this test, we regress either student grades or an indicator for passing on teacher grade inflation measures, separately by subject, controlling for the same observables as in Equation 1:

$$Grade_{ijst} = \delta_{mean}\widehat{GI}_{jt}^{mean} + \alpha_1 TestScore_{ijst} + \alpha_2 Grade_{ist-1} + X_{ist}\alpha + \eta_{ijst}$$

$$Pass_{ijst} = \delta_{pass}\widehat{GI}_{jt}^{pass} + \gamma_1 TestScore_{ijst} + \gamma_2 Grade_{ist-1} + X_{ist}\gamma + \xi_{ijst}.$$

[30]Both tests use our main jackknifed estimates of mean and passing grade inflation, which use all other years of data to estimate grade inflation $\widehat{GI}_{jt}$ in a given year.

In these regressions, $1-\widehat{\delta}$ gives the estimate of forecast bias. An estimate of δ close to one, therefore, shows that any estimation error inherent in the grade inflation measures is not large enough to prevent them from being predictive of student grades and passing out of sample. This high degree of predictive power results in lower forecast bias.

Panels A and B of Table 3 present the results of this test in the LAUSD and Maryland, respectively. Our estimates indicate that both of the grade inflation measures show only small amounts of forecast bias across both subjects and samples. In this first test, our estimates of forecast bias range from 0.03 to 0.11, suggesting our measures are quite predictive of student outcomes. These magnitudes are similar to estimates from the value-added literature.[31]

The second test addresses the concern of selection by testing whether selection on a set of predictors omitted from the estimation equation leads to bias in our grade inflation measures (Chetty et al., 2014a; Rothstein, 2014). In both the LAUSD and in Maryland, we use twice-lagged measures of math GPA, English GPA, total GPA, fraction of days absent, and suspension indicator as omitted predictors. In the LAUSD, we also include twice-lagged standardized test scores; in Maryland, we also include student demographics: race, gender, and free and reduced price lunch (FRPL) status. To conduct this test, we begin by residualizing the predictors (twice-lagged values and demographics) and the outcomes (grade and passing indicator) on the same set of controls used when estimating the teacher grade inflation measures.[32] We then regress the residualized outcome on the residualized predictors and construct fitted outcomes $\widehat{Grade}$ and $\widehat{Pass}$. Finally, we conduct the forecast bias test by regressing the fitted outcomes on our teacher measures:

$$\widehat{Grade}_{ijst} = \nu_{mean}\widehat{GI}_{jt}^{mean} + \eta'_{ijst}$$
$$\widehat{Pass}_{ijst} = \nu_{pass}\widehat{GI}_{jt}^{pass} + \xi'_{ijst}.$$

The estimates of $\widehat{\nu}$ represent estimates of forecast bias, where values of $\widehat{\nu}$ close to zero reflect less selection, and therefore less forecast bias, due to omitted observables.

Panels C and D from Table 3 show the results of the second test. Again, across subjects,

[31] For example, Kane and Staiger (2008) obtain forecast bias estimates of 0.06 to 0.17 when testing measures of value-added for Kindergarten students; Chetty et al. (2014a) obtain estimates of 0.02 to 0.05 for students in grades 3-8.

[32] Those controls include school, grade, and year fixed effects, English Language Learner status, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back.

outcomes, and samples, we estimate very low levels of forecast bias in our grade inflation measures. The forecast bias estimates range from 0.00 to 0.01 in absolute value, indicating that our measures do not suffer from selection on omitted predictors.

Together, these tests suggest that our grade inflation measures are predictive of instructor grading behavior and do not suffer from unobserved selection. Establishing these patterns is important not only for the use of these measures of grade inflation in this paper, but also for any future work that may use these measures.

3.3 Constructing Other Measures of Teacher Quality

In order to understand how related our measures of grade inflation are to more common indicators of teacher quality, we construct both cognitive (test score) and noncognitive value-added measures. We construct jackknife empirical Bayes estimators for cognitive value-added following Chetty et al. (2014a) and noncognitive value-added following Petek and Pope (2023). We create four different noncognitive value-added measures in both the LAUSD and in Maryland: absences, suspension, grade retention and total academic GPA. In the LAUSD, we are able to create two additional noncognitive value-added measures: cooperation GPA and effort GPA. Due to concerns about teachers affecting these noncognitive measures directly, we follow Petek and Pope (2023) and use outcomes measured in the year after the student and teacher interact.

We form student-year level measures of value-added in a similar way to our student-year level measures of grade inflation. We first estimate test score and noncognitive teacher value-added measures for each teacher-subject-year observation, standardized to have mean zero, standard deviation one within year.[33] We then combine math and English test score value-added into a single "cognitive value-added" measure by summing across subjects and standardizing to be mean zero, standard deviation one. Similarly, following Petek and Pope (2023), we combine math and English course measures of days absent, suspension, grade retention, total academic GPA, cooperation GPA, and effort GPA[34] into a single "noncognitive value-added" measure by summing the components and standardizing to be mean zero, standard deviation one. We also create subject-specific noncognitive value-added measures by summing the components from only teachers in

[33] Again, we exclude students in years when they have more than one math instructor or more than one English instructor.

[34] The cooperation and effort GPAs are only available in the LAUSD.

that subject and standardizing to be mean zero, standard deviation one.

For comparison with prior empirical work on grading leniency, we also replicate the measures from Figlio and Lucas (2004) and Gershenson et al. (2022). We construct the measure in Figlio and Lucas (2004) by regressing normalized standardized test scores on course grades and a teacher-year fixed effect. We construct the measure in Gershenson et al. (2022) by regressing normalized standardized test scores on twelve grade indicators, which group students into equal-width bins based on their course grade, and a teacher-year fixed effect. In both cases, the teacher-year fixed effect is the grading leniency estimate. When conducting bias tests, we construct empirical Bayes estimates using similar methods as for our other measures. We do not include our standard vector of controls when forming the Figlio and Lucas (2004) and Gershenson et al. (2022) measures because they do not control for those variables.[35]

Our method of measuring teacher grade inflation differs in important ways from Figlio and Lucas (2004) and Gershenson et al. (2022). We predict grade as a function of test score and teacher, whereas they predict test score as a function of grade and teacher. Our approach follows from a structural model in which a student's measured performance in a course (their grade) is a function of their underlying academic performance (their test score and prior performance in that subject) combined with whatever discretion the teacher has in assigning the grade, which we call grade inflation. While their measures are highly correlated with each other (0.99), the correlation with our measures of grade inflation is weaker, as Table A.1 reports.[36] We estimate that their measures are correlated with our measure of mean grade inflation at -0.67 in the LAUSD and -0.57 in Maryland. Their correlation with passing grade inflation is smaller, ranging from -0.53 to -0.51 in the LAUSD and -0.18 to -0.17 in Maryland. In contrast, their measures are more highly correlated with cognitive value-added, at 0.76 in the LAUSD and 0.67 in Maryland. Empirically, their measures are more similar to traditional value-added than our measure of grade inflation. Specifically, test score value-added and the measures in Figlio and Lucas (2004) and Gershenson et al. (2022) both use test scores as the dependent variable. The key difference between value-added and the measures in Figlio and Lucas (2004) and Gershenson et al. (2022) is that Figlio and Lucas (2004) and Gershenson et al. (2022) control for contemporaneous grades rather than prior

[35]Our empirical Bayes versions of their measures do include year fixed effects.

[36]These correlations are constructed using methods that we describe in Section 3.4. Raw correlations between measures are similar.

test scores.

Neither Figlio and Lucas (2004) nor Gershenson et al. (2022) investigate the forecast bias properties of their measures. Our versions of their measures perform well on the first forecast bias test to address concerns with estimation error, as shown in Table A.2. However, Table A.3 shows that their estimates perform poorly on the second test, revealing bias due to selection on omitted student observables. In particular, the tests estimate bias in the range of 0.25 to 0.68 due to selection on lagged and twice-lagged test scores. Again, these measures are conceptually similar to modern measures of teacher test score value-added, but they control for contemporaneous grades instead of lagged test scores. This omission of a key control likely leads to the bias.

Our grade inflation measures are more similar to the measure found in Mozenter (2019), who also puts grades on the left hand side of the estimating equation. Mozenter (2019) also controls for contemporaneous test scores, and additionally controls for peer averages in contemporaneous test scores, and a student's ordinal class rank in standardized tests. Unlike our measures, Mozenter (2019) does not control for past characteristics, such as past standardized test scores and past grades.

Overall, while there are many similarities between our mean grade inflation measure and the measures put forth by Figlio and Lucas (2004), Gershenson et al. (2022) and Mozenter (2019), there are also important differences. We view our work as building on the prior work, introducing measures that appear to have more desirable properties, and expanding on that work by introducing a measure of passing grade inflation that is complementary to mean grade inflation.

3.4 Estimating Correlations Between Teacher Measures

In order to understand how grade inflation is related to other teacher characteristics, we estimate correlations between our measures of grade inflation and value-added. As described in Jackson et al. (2024), simple ("raw") correlations between estimates of value-added may be biased in either direction. The correlations may be too small because of measurement-error-induced noise in grade inflation and value-added measures. They may instead be too large if those measurement errors are correlated across measures within the same year.

To address these challenges, we estimate the correlation between teacher measures using a split-sample bootstrapping approach. Splitting the sample before estimating grade inflation or value-added resolves the concern of within-year correlations in measurement error. To estimate the correlation between generic teacher measures μ_A and μ_B (where the subscripts denote different teacher quality measures such as mean grade inflation and cognitive value-added), we begin by randomly splitting the sample within classroom.[37] We then estimate teacher measures $\widehat{\mu}_A$ and $\widehat{\mu}_B$ separately in both halves of the sample. This produces two estimates for each measure, for a total of four objects, $\widehat{\mu}_A^0$, $\widehat{\mu}_A^1$, $\widehat{\mu}_B^0$, and $\widehat{\mu}_B^1$, with the superscripts denoting the two halves of the sample. Next, we estimate the across-sample correlation between the measures as

$$\widehat{\rho}_{AB}^{01} = corr\left(\widehat{\mu}_A^0, \widehat{\mu}_B^1\right).$$

We then adjust this correlation for measurement error attenuation by dividing by the product of the within-measure, across-sample correlations $\widehat{\rho}_A^{01} = corr\left(\widehat{\mu}_A^0, \widehat{\mu}_A^1\right)$ and $\widehat{\rho}_B^{01} = corr\left(\widehat{\mu}_B^0, \widehat{\mu}_B^1\right)$. The adjustment results in $\widehat{r}_{AB}$, an unattenuated estimate of the correlation between the teacher measures:

$$\widehat{r}_{AB} = \frac{\widehat{\rho}_{AB}^{01}}{\sqrt{\widehat{\rho}_A^{01}\widehat{\rho}_B^{01}}}.$$

Note that each sample split will produce two estimates of the correlation: $\widehat{r}_{AB}$ and $\widehat{r}_{BA}$, which need not be numerically identical. To obtain our actual correlation estimates, we bootstrap this quantity by splitting the sample in half 100 times and averaging across the 200 resulting estimates.

3.5 Estimating the Effects of Teacher Grade Inflation

To explore the effects of grade inflation on future outcomes, we estimate specifications similar to Chetty et al. (2014b), Petek and Pope (2023), Gershenson et al. (2022), Figlio and Lucas (2004), and Mozenter (2019), where an observation is a student-year and we regress an outcome on the mean and passing grade inflation measures, the cognitive and noncognitive value-added measures, and the same set of controls used to construct these measures. In particular, we estimate the following equation:

$$Y_{it} = \theta_{mean}\widehat{GI}_{it}^{mean} + \theta_{pass}\widehat{GI}_{it}^{pass} + \delta_{cog}\widehat{VA}_{it}^{cog} + \delta_{noncog}\widehat{VA}_{it}^{noncog} + X_{it}\beta + \eta_{it} \tag{2}$$

[37] This within-classroom splitting approach was inspired by the student-level correlation estimation procedures in Ayllón et al. (2025).

where Y_{it} is a future outcome, such as graduation from high school or test score performance in the following year, $\widehat{GI}_{it}^{mean}$ is the average measure of mean grade inflation a student experiences in year t, $\widehat{GI}_{it}^{pass}$ is the average measure of passing grade inflation a student experiences in year t, $\widehat{VA}_{it}^{cog}$ and $\widehat{VA}_{it}^{noncog}$ are the average measures of cognitive and noncognitive value-added a student experiences in year t, and X_{it} is the same vector of student controls used when estimating grade inflation in Equation 1.[38]

In our main results, we use versions of grade inflation and value-added that average over the subject-specific measures, as described in Sections 3.1 and 3.3. We also explore whether the effects of grade inflation differ in math and English classes. In those specifications, we use the subject-specific versions of our grade inflation and value-added measures. In all cases, the grade inflation and value-added measures have been standardized to mean zero, standard deviation one to facilitate interpretation.

In regressions based on Equation 2, an observation is a student-year. We cluster our standard errors at the school level to account for within-school correlation in outcomes. The coefficients of interest are θ_{mean} and θ_{pass} which estimate the effects of mean and passing grade inflation after accounting for other student and teacher characteristics. We interpret θ_{mean} as the general effect of easier standards after accounting for teachers' propensity to pass students. As we noted above, Costrell (1994); Betts (1998) show that the effects of grade inflation are theoretically heterogeneous. We interpret θ_{mean} as the average of these potentially heterogeneous effects across students. Additionally, we interpret θ_{pass} as the effect of grade inflation that primarily arises through the policy implications of receiving a passing grade (i.e., receiving credit for a class).

We also report δ_{cog} and δ_{noncog} in many specifications to verify that our measures of teacher value-added have the expected estimated effects and to compare magnitudes. In all regressions, we limit our sample as described in Section 2, requiring students to have the necessary information to construct grade inflation and value-added measures, and requiring each student-year observation to have at most one math teacher and at most one English teacher. In addition, in the LAUSD we implement sample restrictions that vary by the availability of the outcome. For example, the California Standardized Tests are only administered through 11$^{\text{th}}$ grade; we therefore exclude 11$^{\text{th}}$

[38]These controls include school, grade, and year fixed effects, an indicator for English language learner (ELL), and previous year math test score, English test score, total academic GPA, fraction of days absent, suspension, and grade retention.

and 12th graders from the analysis when future test score is the outcome variable. In Maryland, because of the different testing protocol, we restrict our analysis to grades 9 through 11 for all high school outcomes. For the post-secondary and career outcomes, we use grades 9 through 12.

4 Results

In this section, we show that grade inflation is a separate characteristic from value-added and that our two measures of grade inflation are related but distinct. We then show that grade inflation matters for students' future outcomes. Mean grade inflation decreases students' future standardized test scores, probability of graduating high school, college enrollment, employment, and earnings. Passing grade inflation reduces the probability of being held back, increases the probability of graduating high school, and increases some postsecondary enrollment. We also show that the effects of grade inflation vary across the performance distribution.

4.1 How is Grade Inflation Related to Other Teacher Characteristics?

Before exploring the relationship between grade inflation and students' future academic and career outcomes, we first characterize the relationship between our measures of teacher grade inflation and other common measures of teacher quality. We show that the two measures we define in Section 3.1 represent related, but distinct aspects of teacher grading standards. Furthermore, we show that these grade inflation measures capture a separate aspect of teacher quality than that captured by traditional cognitive and noncognitive value-added measures.

Table 4 presents correlations of our two measures of grade inflation with two measures of teacher value-added: cognitive and noncognitive. All correlations are calculated using the method described in Section 3.4 to avoid bias due to measurement error. These correlations are inherently not causal, but rather reflect the extent to which grade inflation and other teacher attributes covary in the observed data.

Because a teacher who raises the grades of all students will also increase the probability of a student passing their class, mean and passing grade inflation should be positively correlated. Our correlation estimates in Table 4 confirm that this relationship holds in both the LAUSD and in Maryland. In the LAUSD, the correlation between mean and passing grade inflation is 0.86.

In Maryland, the correlation is notably lower, around 0.36. This lower estimated correlation in Maryland is likely explained by the low fail rates in Maryland,[39] which translates into less variation in the passing grade inflation measure. Nevertheless, in both settings, the two measures are not perfectly correlated – passing grade inflation and mean grade inflation appear to be distinct attributes.

Table 4 also presents estimates of the correlation between teachers' grade inflation and value-added measures. Teachers who inflate grades tend to have lower cognitive (test score) value-added. Mean grade inflation is negatively correlated with cognitive value-added, with correlations of -0.41 in the LAUSD and -0.31 in Maryland. This negative correlation is consistent with Betts and Grogger (2003), Figlio and Lucas (2004), Mozenter (2019), and Gershenson et al. (2022), who find that grade-inflating teachers reduce test scores. Passing grade inflation is also negatively correlated with cognitive value-added. The correlations are weaker than those with mean grade inflation, with estimated correlations of -0.30 and -0.07 in the LAUSD and Maryland, respectively. In contrast, both mean and passing grade inflation are weakly positively correlated with noncognitive value-added. The correlation between mean grade inflation and noncognitive value-added is 0.16 in the LAUSD and 0.12 in Maryland. The correlation between passing grade inflation and noncognitive value-added is 0.18 in the LAUSD and 0.05 in Maryland.

Because numerous studies cite teacher experience as a correlate with achievement gains (Kini and Podolsky, 2016), we also test whether grade inflation is correlated with experience. We find that both in the LAUSD and in Maryland, grade inflation is mildly negatively correlated with experience. The correlations are stronger in the LAUSD, from -0.09 to -0.15 depending on subject and measure, than in Maryland, ranging from -0.01 to -0.05. Our teacher experience measure is limited: we use the number of years a teacher is observed in the data.[40] This evidence suggests that teachers may inflate grades less as they gain experience in teaching.

[39]Only 3.1% of math courses and 2.3% of English courses are failed by Maryland students, compared to 32% and 21% in the LAUSD.

[40]We also construct the correlation using only teachers who appear in the data after the first year and find very similar results.

4.2 Does Grade Inflation Matter for Future Outcomes?

The correlations between grade inflation and value-added suggest that grade inflation represents a distinct teacher characteristic from typical value-added metrics. If our estimated correlations contain a causal component, a teacher's decision to inflate grades could carry tradeoffs because grade inflation is both positively and negatively correlated with other desirable teacher characteristics. For instance, a grade-inflating teacher might induce students to attend class more, but reduce student learning as measured by test scores. Inflating grades could even be the optimal choice to maximize certain student outcomes.

To explore whether grade inflation has positive or negative impacts on students' cognitive and noncognitive performance, we estimate the effect of teachers' grade inflation decisions on high school, college, and career outcomes. We begin with simple regressions of the relevant student outcome on just one of our measures of teacher characteristics (mean or passing grade inflation or cognitive or noncognitive value-added) at a time. Unless otherwise stated, all regression analyses discussed here and in later sections control for the same student characteristics used to create the grade inflation and value-added measures, which are school, grade, and year fixed effects, ELL status, previous math test score, previous English test score, previous total academic GPA, previous fraction of days absent, previous suspension, and previous grade retention. Standard errors are clustered at the school level.

The results of the simple regressions with one measure at a time, shown in Table 5, verify that when considered in isolation, the associations between teacher value-added measures and student outcomes generally have the expected sign.[41] Higher cognitive value-added is associated with increases in test scores, SAT scores, and the likelihood of graduating. Higher noncognitive value-added is associated with reductions in the likelihood a student is held back and increases in the likelihood of graduating. The direction of these associations is consistent with the existing literature. In addition, we estimate that grade-inflating teachers are associated with reductions in future test scores, SAT scores, and the likelihood that a student is held back. However, these results do not separately identify the impact of grade inflation while holding other teacher characteristics (i.e., value-added) fixed. That is, the negative relationship between grade inflation and student

[41] Appendix Table A.4 reports similar associations for the postsecondary and employment outcomes in Maryland.

outcomes estimated in Table 5 could simply reflect the negative correlation between grade inflation and cognitive value-added rather than any causal effect of grade inflation on outcomes.

To disentangle these relationships, in our main results we explore whether grade inflation matters for future outcomes *conditional on other teacher characteristics* by estimating Equation 2. We include mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added in each regression. This allows us to identify the effect of each teacher characteristic on student outcomes while holding constant other teacher characteristics.

Before describing our estimates of the effects of grade inflation, we briefly discuss cognitive and noncognitive value-added to verify that the estimated coefficients have the expected magnitude and direction. Table 6 shows our estimates of the effects of value-added on high-school outcomes, conditional on other teacher measures. In the LAUSD, having teachers with higher cognitive value-added improves future end-of-year standardized test scores, SAT scores, the likelihood of graduating, and the likelihood of taking the SAT. In Maryland, the estimated effects of cognitive value-added are similar, though the relationships with graduation rates and with SAT scores are absent. In both the LAUSD and Maryland, having teachers with higher noncognitive value-added improves future English test scores, reduces the likelihood of grade retention, and increases graduation rates. In the LAUSD, noncognitive value-added also increases the likelihood of taking the SAT. In addition, noncognitive value-added slightly reduces future SAT scores in Maryland. These results closely mirror those of Petek and Pope (2023).

High School Outcomes

Having determined that Equation 2 yields sensible estimates for well-established value-added measures, we turn to estimating the effects of mean and passing grade inflation on high school outcomes conditional on other teacher characteristics. Table 6 presents estimates for our main high school outcomes, which are future math and English test scores, the likelihood of being held back, the likelihood of graduating within five years, the likelihood of taking the SAT, and SAT score. Tables A.5 and A.6 present estimates for additional high school outcomes such as absences, suspensions, and PSAT scores.

We find that conditional on other teacher characteristics, mean grade inflation reduces future test scores. In the LAUSD, we find that a one standard deviation increase in the amount of mean grade inflation a student is exposed to in one year reduces future math test scores by 0.024 standard deviations and future English test scores by 0.021 standard deviations. In comparison, being exposed to higher cognitive value-added teachers increases future test scores by 0.118 for math and 0.058 for English. Comparing the grade inflation and value-added estimates, a teacher's grading leniency has a meaningful impact on future test score performance – about 20 percent as large as the effect of traditional value-added measures in math and 36 percent as large in English. This finding is similar to the results of Figlio and Lucas (2004) and Gershenson et al. (2022). The effect of mean grade inflation on future test scores is substantially smaller in Maryland. However, standardized testing during high school is much more frequent in the LAUSD than in Maryland.[42]

Beyond future test scores, mean grade inflation also impacts other high school outcomes. We estimate that mean grade inflation reduces the chance that a student takes the SAT by 0.5 percentage points in both the LAUSD and Maryland. However, in both locations, we find no effect of mean grade inflation on SAT scores. Finally, we find that mean grade inflation reduces the likelihood of graduating high school within 5 years by 0.8 percentage points in the LAUSD and 0.1 percentage points in Maryland. Because five-year graduation rates are much higher in Maryland than in the LAUSD (91 percent and 55 percent, respectively), the smaller effect of mean grade inflation on graduation in Maryland could be explained by differences in the marginal student at risk of not graduating. In Tables A.5 and A.6 we also show that mean grade inflation increases absences and suspensions in both the LAUSD and in Maryland.

Passing grade inflation affects these educational outcomes differently than mean grade inflation. First, we find that passing grade inflation has no effect on future test scores in math or English. In addition, passing grade inflation appears to be beneficial for some other outcomes. We estimate that being exposed to a one standard deviation higher passing grade-inflating teacher reduces the likelihood of being held back by 1.2 percentage points in the LAUSD and 0.4 percentage points in Maryland. Because being held back is a rare event in both the LAUSD and in Maryland,[43] our estimates imply a meaningful effect size, representing about a ten percent decline in the likelihood of repeating a grade. We also estimate that passing grade inflation increases the likelihood of

[42]The LAUSD administers standardized tests yearly through 11th grade, whereas Maryland high school students take standardized math and English tests in only about two years of high school. Algebra I, Algebra II, Geometry, and either 9th or 10th grade English are the standardized tests administered in Maryland.

[43]Being held back is defined as having the same administrative grade level code in the current and previous year. About 11 percent of students in our LAUSD sample and 4 percent of students in our Maryland sample are held back.

graduating within five years by 0.5 percentage points (p<.1) in the LAUSD and 0.2 percentage points in Maryland. We find no effect of passing grade inflation on taking the SAT.

In summary, the results of our analysis show that our more traditional measure of mean grade inflation reduces educational outcomes in high school, evidenced by lower test scores in the following year and a lower probability of graduation. This is consistent with reductions in learning associated with muted incentives that arise from easier grading. In contrast, passing grade inflation offers potential policy benefits for students by decreasing grade retention and increasing the probability of graduating high school. However, from this evidence alone, it is not clear whether these higher rates of high school completion brought about by passing grade inflation are beneficial to students in the longer term. We turn to our analysis of college and early career outcomes to investigate the longer-term effects of grade inflation.

Longer Term Outcomes

Using Maryland's linked K-12, college, and employment data, we explore the impact of mean and passing grade inflation experienced during high school on college enrollment, college graduation, earnings, and employment. In this analysis, we estimate the effect of grade inflation on college and career outcomes measured at different times relative to the students' expected high school graduation in order to capture any dynamic effects of the two grade inflation measures. This means that the sample is composed of different cohorts for different outcome measures. For example, when the outcome is being enrolled in any postsecondary education one year after expected high school graduation, our data includes students who were in 12$^{\text{th}}$ grade in 2013 through 2022, whereas when enrollment is measured eight years after expected high school graduation, only 12$^{\text{th}}$-grade cohorts 2013 through 2015 are included.

We find that the effects of grade inflation extend into early adulthood via postsecondary education.[44] Table 7 displays these results, where we estimate that mean grade inflation reduces enrollment in any postsecondary schooling by 0.6 percentage points in the year after expected high school graduation, but has no measurable effect on the likelihood of graduating from postsecondary schooling. We investigate further by evaluating the effect of mean grade inflation on two-

[44]This is similar to results from the value-added literature. For example, Chetty et al. (2014b) found that test score value-added in elementary and middle school affects students' college-going and earnings.

year and four-year colleges separately. Our estimates in Panel A of Table 8 show that mean grade inflation reduces enrollment in Associate's degree programs one to seven years beyond expected high school graduation. For Bachelor's degrees, Panel B shows that mean grade inflation reduces enrollment three to six years after expected high school graduation. While mean grade inflation reduces enrollment in both Associate's and Bachelor's degree programs, Table 9 shows that its impact on completion differs by degree program. Mean grade inflation reduces Associate's degree completion but has no effect on Bachelor's degree completion.

The effects of passing grade inflation on students' postsecondary education differ from those of mean grade inflation. Table 7 shows that passing grade inflation does not affect enrollment in postsecondary education one year after graduation and ultimately decreases graduation both four and six years after expected high school graduation. Again, Tables 8 and 9 split the analysis by type of degree to reveal interesting patterns. Passing grade inflation increases enrollment in Associate's programs one to five years after expected high school graduation, but has no strong effect on graduation from those programs. Passing grade inflation has a negative effect on enrollment in and graduation from Bachelor's degree programs. The net effect is that passing grade inflation brings about no change overall in any postsecondary enrollment and no statistically significant effect on overall degree attainment.

Grade inflation also affects students' labor market outcomes. Table 7 presents the effects on employment and earnings one and six years after expected high school graduation and Table 10 shows dynamic effects from one through eight years after expected high school graduation. Mean grade inflation reduces employment one to four and six years after expected high school graduation as measured by having any positive wages in at least one quarter of the year. Exposure to one standard deviation higher mean grade inflation in one year of high school reduces the probability of employment by 0.2 to 0.4 percentage points. In Table 10, we also impose a stricter criterion of working at least two quarters of the year to exclude those who only work a summer job while in college and find slightly stronger effects of a 0.3 to 0.5 percentage point reduction in the first four years. Passing grade inflation has a statistically significant positive effect on being employed in two or more quarters in the year by 0.2 to 0.3 percentage points in the first four years after expected high school graduation.

Because mean grade inflation affects the extensive margin of employment, we focus our earnings analysis on unconditional earnings winsorized at the 99^{th} percentile. We find that mean grade inflation reduces earnings by about $56 to $145 a year from one through six years after expected high school graduation. As previously noted, we lose cohorts of students for longer-term outcomes, and by year 7, we have lost approximately 70 percent of our sample. We estimate a small positive relationship between passing grade inflation and earnings of similar magnitude to the negative relationship between mean grade inflation and earnings, though it is only statistically significant one through three years after expected high school graduation. This may be because students are more likely to have high school degrees, which have some value in the labor market. Because the effect fades out, this is consistent with a signaling interpretation of high school diplomas where employers learn about student skill over time (Altonji and Pierret, 2001).

Our exploration of the longer-term impacts of mean and passing grade inflation suggests that the negative effects of mean grade-inflating teachers persist into young adulthood. These results are consistent with the hypothesis that mean grade inflation reduces human capital accumulation. However, passing grade inflation shows more muted long-term effects, with some suggestion of a shift away from four-year and toward two-year college enrollment and increases in earnings in the first few years after expected high school graduation.

4.3 Interpretation

In interpreting these results, a few things are worth bearing in mind. It may be that being assigned a teacher with higher grade inflation in one year is correlated with future assignment to higher grade inflating teachers. This could occur if teacher grade inflation is correlated with tracking. However, we find limited evidence of year-to-year persistence in grade inflation. We calculate the one year autocorrelation of average grade inflation measures within student, adjusting for controls. In Maryland, the autocorrelation of grade inflation is virtually zero and not statistically significant for both mean and passing grade inflation. In the LAUSD, the correlations are statistically significant, but still small in magnitude, with autocorrelations of about 0.14 for both mean and passing grade inflation. This is an interesting finding in and of itself, but also aids in the interpretation of our results. We are estimating the effect of being exposed to a higher grade-inflating teacher in one year, and that exposure is not very predictive of a student's exposure to future (or past) grade inflation. Hence, our coefficients represent the effect of one student's exposure in one year.

Although our estimates represent the effect of a one year, one standard deviation increase in exposure to grade inflating math and English teachers on a single student's future outcomes, teachers affect many students in a single year. We can carry out a simple calculation, making some simplifying assumptions, to better understand the magnitude of these effects. For this exercise, we focus on the effect of a teacher's mean grade inflation decisions on earnings. In our Maryland sample, the typical math teacher teaches 93 students and the typical English teacher teaches 89 students in one year.[45] To illustrate the total effect of a single teacher's propensity to mean grade inflate in one year, we take the average estimated effect, in percent terms, of mean grade inflation on earnings one through six years after expected high school graduation, multiply by the average number of students a teacher sees and the present discounted value of lifetime earnings, and divide by two since our main measures represent the average of approximately two teachers' grade inflation.[46] Our estimates imply that reducing mean grade inflation by one standard deviation for one teacher in one year would increase the present discounted value of earnings of their students by $213,872.

4.4 Heterogeneity

In the previous sections, we focused on the average effects of mean and passing grade inflation. However, the effects of grade inflation may vary for different types of students. For instance, holding mean grade inflation fixed, passing grade inflation is more relevant to students who are on the margin of passing a class. Additionally, mean grade inflation might reduce human capital formation to a larger degree for top students who can reduce their effort and still receive an A. On the other hand, the incentive effects induced by mean grade inflation likely apply to all students, since students need to study less to earn a B, C, or D as well.

We test whether the effects of mean and passing grade inflation vary for different types of students by estimating Equation 2 on separate samples split by a variety of student and school characteristics.[47] In Tables 11, 12, and 13, we explore whether lower-achieving students are more

[45]In the LAUSD sample, the typical math teacher teaches 129 students and the typical English teacher teaches 98 students in one year.

[46]We use $522,000 from Chetty et al. (2014b) for the present discounted value of earnings; calculate the effect in percent terms as 0.009 from Table 7 by looking at the increase in wages relative to the mean wages; and take the average class size of 92.

[47]Note that unlike Eastmond et al. (2026), we still estimate our teacher measures on the full sample of students. Only

or less impacted by grade inflation than higher-achieving students. We use 8^{th} grade GPA as a measure of achievement that is, importantly, captured before students enter high school and therefore not impacted by high school teacher grade inflation.[48] Panel C of each table presents p values from tests for a difference between the below-median and above-median estimates for each measure and outcome. Values less than 0.05 suggest outcomes for which there is strong evidence that grade inflation impacts below- and above-median achievers differently.

First, we find that mean grade inflation reduces future test scores for both above- and below-median students. Our tests, with p values between 0.15 to 0.78 in the LAUSD and 0.22 to 0.52 in Maryland, give no evidence that the estimated effect of grade inflation on future test scores differs by student achievement. We conclude, therefore, that the reduction in human capital due to mean grade inflation occurs at all parts of the student achievement distribution. Heterogeneity in mean grade inflation's effect on SAT taking and scores differ between the LAUSD and Maryland. In the LAUSD, mean grade inflation has no differential effect on scores, but we see larger declines in SAT taking for above-median students, with a p value of 0.06. In Maryland, mean grade inflation decreases SAT taking for all students, and reduces test scores more for below-median students, with a p value of 0.0002.

Second, we find heterogeneity in the effects of grade inflation on graduation and persistence among students of different academic abilities. Our tests suggest that the estimated effects of passing grade inflation on grade retention and graduation are larger for below-median students than for above-median students, with p values of 0.099 in the LAUSD and 0.03 in Maryland for grade retention and p values of 0.027 both the LAUSD and in Maryland for graduation. The differences between above- and below-median students are larger for graduation than grade retention in both samples. This is consistent with intuition because above-median students are not close to the passing margin. We also find that mean grade inflation reduces grade retention more among below-median students, with p values of 0.027 in the LAUSD and 0.0004 in Maryland.

Third, we find few differences in the effects of grade inflation on the longer-term outcomes of lower- and higher-ability students. The biggest difference is in enrollment in postsecondary education. We find that mean grade inflation reduces enrollment more among below-median stu-

the outcome regressions are estimated separately.

[48]We explored using more information to predict which students were more at risk of failing, but we did not see meaningful increases in power to detect differences across groups.

dents, with p values from 0.004 to 0.009. We generally do not see statistically significant differences between lower- and higher-ability students students for earnings.

We examine several other dimensions of heterogeneity. First, we explore heterogeneous effects by school-level grading patterns, measured by school average GPA, to account for different grading contexts. Second, we explore heterogeneity by student characteristics in Maryland.[49] We split the sample by English Language Learner status, Free and Reduced Price Meal status, gender, and race. We do not find strong evidence of heterogeneity across either the school or student characteristics.[50]

4.5 Robustness

Carrying out our analysis in both the Los Angeles Unified School District and the state of Maryland provides an effective robustness check for our main results. These two settings differ in many ways, including the demographic makeup of students, curriculum, and the amount of funding, and yet we find similar patterns. Between the two, we have evidence from a large urban school district on the West Coast with a large Hispanic population, and a populous East Coast state with a range of school districts from small rural areas to larger urban areas. In both the LAUSD and in Maryland, we find that mean grade inflation reduces high school achievement, graduation, and the likelihood of taking the SAT, while passing grade inflation decreases grade retention and increases graduation. We view this consistency across samples as the strongest evidence that our findings are not the result of a particular institutional context.

As a supplement to carrying out our analysis in two settings, we explore the robustness of our specifications in several ways. First, we explore whether our choice of controls impacts our results. In Maryland, we have rich demographic data on students, which we use to augment our controls in both the construction of the value-added and grade inflation measures and in the estimation of the effects of those measures on high school, college, and career outcomes. As Tables A.7 and A.8 show, the estimates remain very similar when we control for these additional student characteristics.

Second, we relax functional form assumptions about the relationship of past test scores by constructing our measures of teacher grade inflation using more flexible test score controls and re-estimating equation 2. In particular, we use a cubic in prior test scores to flexibly control for student

[49] The LAUSD data does not contain the rich student demographics necessary for this analysis.
[50] The results of these heterogeneity analyses are all available upon request.

achievement. These results appear in Tables A.9 and A.10. We find generally similar results with a small loss in precision.

Third, we explore whether our results are consistent across math and English courses. Our main analysis is based on a combined sample of math and English teachers in which we create the value-added and grade inflation measures separately for math and English teachers, then combine across subjects to form a single measure of the average cognitive value-added, noncognitive value-added, and grade inflation experienced by a given student over all math and English courses in a given year. [51] Because high school teachers specialize in one subject and not all students take math and English courses in all years, combining the measures across math and English increases our sample size. However, as a robustness check, we also carry out analysis with measures of grade inflation and value-added that are specific to math or English. The main results from these analysis are found in Tables A.11, A.12, and A.13. We find generally similar patterns, but with slightly less precision. The effects of grade inflation do not appear to be driven primarily by either math or English teachers.

Fourth, it could be that contemporaneous subject test scores are "bad controls" in the estimation of our grade inflation measures because they are also influenced by the teacher. We re-estimate our grade inflation measures omitting contemporaneous test scores and find very similar results. Table A.14 shows that our preferred measures of grade inflation and measures that omit contemporaneous test scores are very highly correlated, with correlations of 0.89 to 0.99. Tables A.15 and A.16 show that the high school and longer term effects of these alternative measures of grade inflation are very similar to our main estimates.

Fifth, we test whether our results are driven by pooling across courses within subject. Our main results pool together many different courses which may have different contexts and varied effects of grade inflation. To focus on a common and consistent context, we re-estimate value-added, grade inflation, and our main outcome regressions using only students in Algebra I. The results are similar to our main estimates, though with less precision, as can be seen in Tables A.17 and A.18.

The robustness of our results to different school districts, different data, different model specifications, and different subjects, demonstrates that the relationship between grade inflation and

[51]See Section 2 for more details.

student outcomes in the short and long term is unlikely to be driven by any particular choice.

5 Conclusion

In this paper, we find that teachers' grading practices affect students in meaningful and heterogeneous ways. A teacher who inflates average grades has a negative effect on students' future performance as measured by test scores, high school graduation, college enrollment, and earnings. In contrast, a teacher who inflates grades so that students are less likely to fail decreases grade retention and improves high school graduation rates. The magnitude of these grade inflation effects varies depending on student characteristics and whether a student is on the margin of passing a course.

Our results align with the theoretical prediction that grades serve as a potent motivator for educational engagement. In light of increasing grade inflation in the United States, our findings suggest that students may be learning less. While our paper does not directly address the change in grading practices over time, our results highlight the potential detrimental impact of increasing grades over time.

Additionally, our results demonstrate that grading practices are another channel by which teachers affect their students' long-term outcomes. While most teacher training programs that improve teacher quality are high-cost and time-consuming (Taylor and Tyler, 2012), changes in grading policies are a potential low-cost strategy that could be implemented by teachers, schools, and school districts to improve teacher quality and students' long-term outcomes.

Grade inflation does not only arise in high school and at the teacher level. This paper leaves open policy questions about school- or system-wide grading interventions or the effects of grade inflation at different levels of schooling, such as middle school or college. It is unclear from our results if policies at different school levels would have the same effects as teacher grade inflation in high school. However, many of the mechanisms highlighted in our paper likely still apply: mean grade inflation changes the incentives for learning at all levels, and passing grade inflation changes the fraction of students subject to the policy effects of course failure at all levels. Indeed, Bowden et al. (2023) finds many similar mechanisms at play from a statewide grade reform. We hope that future work considers the effects of grade inflation at different levels of education directly.

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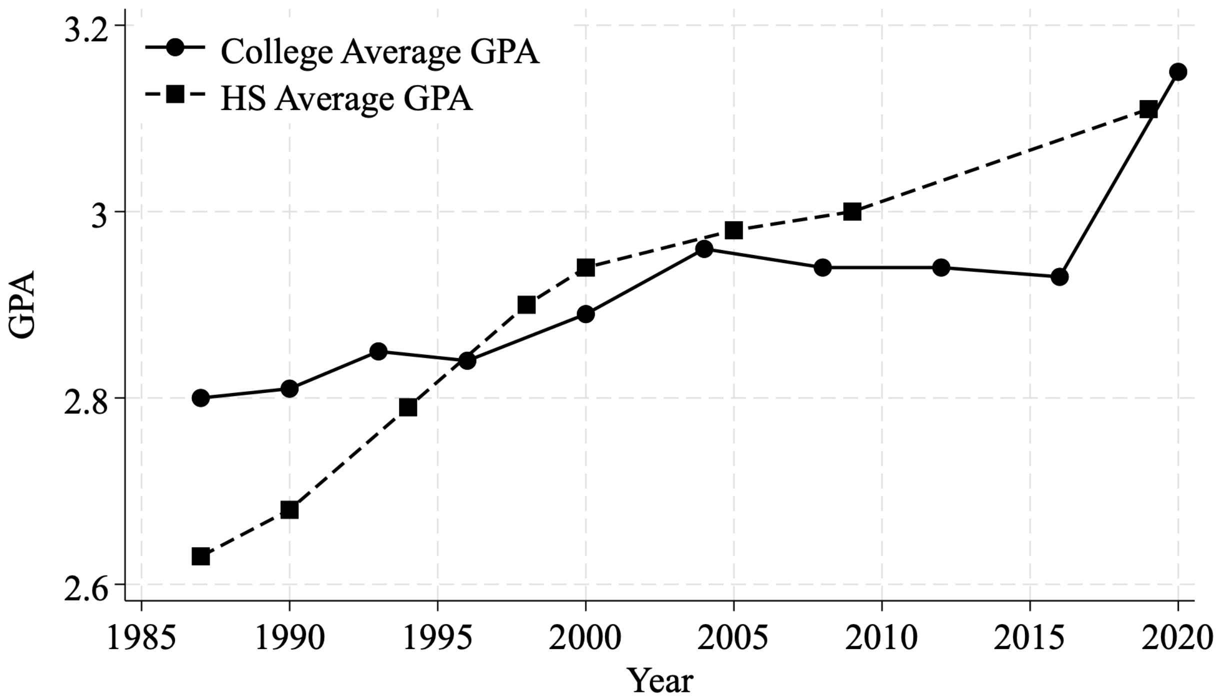
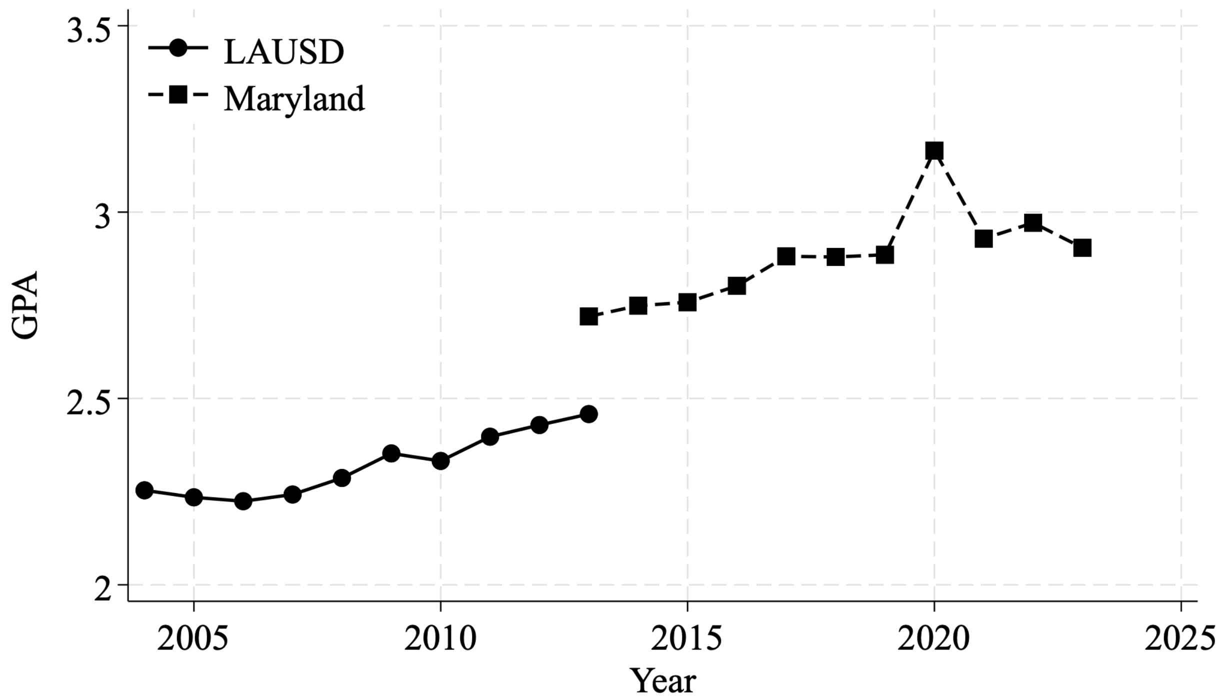
6 Tables and Figures

Figure 1: Average High School and College GPA over Time



Notes: This figure plots the average total GPA over time for both high school and college students. The figure uses data from the High School Transcript Study from the National Center for Education Statistics for high school students. For college students, the figure uses data from the National Postsecondary Student Aid Study from the National Center for Education Statistics. GPA is measured on a 0 to 4 scale (e.g., A = 4.0, B = 3.0).

Figure 2: Average Maryland and LAUSD GPA over Time



Notes: This figure plots the average total GPA over time for students in the LAUSD and Maryland samples. The data from the LAUSD span 2004 to 2013 and the data from Maryland span 2013 to 2023. GPA is measured on a 0 to 4 scale (e.g., A = 4.0, B = 3.0).

Table 1: Student-level Summary Statistics in the LAUSD

	Mean	Std. Dev.	N
Math CST Score	0.08	1.03	631,535
English CST Score	0.15	1.00	668,056
Math GPA	1.79	1.25	816,284
English GPA	2.22	1.21	868,217
GPA	2.33	0.98	868,217
Effort GPA	2.18	0.53	868,217
Cooperation GPA	2.41	0.45	868,217
Fraction of Days Absent	0.07	0.09	868,217
Ever Suspended	0.06	0.24	868,217
Held Back	0.11	0.32	868,217
English Learner	0.18	0.39	868,217
Average Teacher Experience	6.56	2.84	868,217
Don't Graduate in LAUSD	0.30	0.46	635,556
Leave Dataset	0.26	0.44	635,556
Graduate on Time	0.46	0.50	726,007
Graduate within 5 Years	0.55	0.50	635,556
Number of AP Courses	1.20	2.12	868,217
Ever Took SAT	0.38	0.49	726,007
Ever Took PSAT	0.43	0.49	576,989
SAT Score	1343.69	300.32	337,935
PSAT Score	112.52	25.94	359,059
English CAHSEE Score	0.18	0.98	756,400
Math CAHSEE Score	0.17	1.01	758,838
10th Grade Science CST Score	0.16	1.02	586,773
11th Grade Social CST Score	0.15	1.01	599,109

Notes: This table reports summary statistics (mean, standard deviation, and number of observations) for all high school students enrolled in LAUSD between 2004-2013. The sample is restricted to students with non-missing test scores, grades, and behavioral outcomes. Test scores (end-of-year standardized tests) are standardized before making sample restrictions. "Held back" is measured as whether we see the student with the same administrative grade code in the following year. "Average teacher experience" is the average number of years a student's teachers have taught for. "Don't graduate in LAUSD" and "Leave Dataset" capture the degree to which the graduation outcomes are censored by the sample time period ending or students moving outside of LAUSD. "CAHSEE" refers to the California High School Exit Examination administered from 2006 to 2014.

Table 2: Student-level Summary Statistics in Maryland

	Mean	Std. Dev.	N
Math Test Score	0.05	0.98	240,309
English Test Score	0.05	0.96	259,395
Math GPA	2.47	1.06	746,027
English GPA	2.67	1.04	801,899
GPA	2.81	0.83	801,899
Frac. Days Absent	0.07	0.09	801,899
Suspended	0.06	0.23	801,899
Held Back	0.04	0.18	801,899
English Learner	0.02	0.13	801,899
Free and Reduced Price Meals	0.35	0.48	801,899
Black	0.36	0.48	801,899
White	0.42	0.49	801,899
Asian	0.07	0.25	801,899
Hispanic	0.12	0.33	801,899
Female or Non-Binary	0.50	0.50	801,899
AP Classes	3.48	4.87	801,899
Honors Classes	7.37	7.37	801,899
Ever Took SAT	0.69	0.46	801,899
Ever Took SAT or ACT	0.73	0.44	801,899
Ever Took PSAT	0.49	0.50	801,899
SAT Score	1255.25	337.68	207,328
PSAT Score	128.03	32.00	135,741
Graduate HS On Time	0.86	0.35	801,899
Graduate HS w/in 5 Years	0.92	0.27	801,899
Enrolled in Any Post-Secondary 1 year Post HS	0.67	0.47	801,899
Enrolled in Any Post-Secondary 2 years Post HS	0.60	0.49	801,899
Graduate Post-Secondary w/in 4 years Post HS	0.27	0.45	677,364
Graduate Post-Secondary w/in 6 years Post HS	0.41	0.49	393,146
Employed 1 year Post HS	0.69	0.46	801,899
Employed 6 years Post HS	0.63	0.48	393,146
Earnings 1 year Post HS	7,244.2	7,067.4	551,434
Earnings 6 years Post HS	27,907.4	21,293.0	247,154

Notes: This table reports summary statistics (mean, standard deviation, and number of observations) for all high school students enrolled in Maryland between 2013-2023. The sample is restricted to students with non-missing test scores, grades, and behavioral outcomes. Math tests are from Algebra I, Algebra II, and Geometry courses; English tests are from grades 9 and 10. Test scores are standardized before making sample restrictions. "Held back" is measured as whether we see the student with the same administrative grade code in the following year. The timing of the college and career outcomes are measured relative to expected high school graduation as of 9th grade, so "1 year post HS" refers to 5 years after we see the student in 9th grade. Earnings are conditional on having observed any earnings and are winsorized at the 99th percentile.

Table 3: Forecast Bias Tests of Grade Inflation

	Math		English	
Panel A: Actual Outcome Variable, LAUSD	Course Grade	Pass Indicator	Course Grade	Pass Indicator
Corresponding GI Measure	1.07	1.07	1.03	1.04
	(0.01)	(0.02)	(0.01)	(0.01)
Observations	468,282	468,410	539,296	539,368
Panel B: Actual Outcome Variable, Maryland	Course Grade	Pass Indicator	Course Grade	Pass Indicator
Corresponding GI Measure	1.08	1.11	1.03	0.96
	(0.02)	(0.07)	(0.02)	(0.21)
Observations	204,944	204,944	250,485	250,485
Panel C: Predicted Outcome Variable, LAUSD	Course Grade	Pass Indicator	Course Grade	Pass Indicator
Corresponding GI Measure	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	198,173	199,904	244,445	244,465
Panel D: Predicted Outcome Variable, Maryland	Course Grade	Pass Indicator	Course Grade	Pass Indicator
Corresponding GI Measure	-0.01	-0.00	-0.01	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)
Observations	46,402	46,402	65,351	65,351

Notes: This table presents results from two different forecast bias tests. The tests in panels A and B regress actual outcomes, identified by column, on jackknifed empirical Bayes estimates of grade inflation measures. The tests in panels C and D regress outcomes, predicted by a set of variables omitted from our standard list of controls, on jackknifed empirical Bayes estimates of grade inflation measures. The omitted variables used in the LAUSD are twice-lagged values of standardized test score, math, English, and total GPA, fraction days absent, suspension, and held back. The omitted variables used in Maryland are the same as in LA but excluding twice-lagged test scores and including race, gender, and FRPL status. Standard errors are clustered at the school level.

Table 4: Correlations between Grade Inflation and Value-Added Measures

Panel A: LAUSD	Mean GI	Passing GI	Cog. VA	Noncog. VA
Mean GI	1.0000	.	.	.
Passing GI	0.8602	1.0000	.	.
Cog. VA	-0.4070	-0.3048	1.0000	.
Noncog. VA	0.1555	0.1783	0.0882	1.0000
Panel B: Maryland	Mean GI	Passing GI	Cog. VA	Noncog. VA
Mean GI	1.0000	.	.	.
Passing GI	0.3592	1.0000	.	.
Cog. VA	-0.3092	-0.0734	1.0000	.
Noncog. VA	0.1161	0.0579	-0.1305	1.0000

Notes: Within-teacher-year correlations are estimated using an error correction procedure based on randomly splitting the data within classroom. Reported correlations are the average across 200 bootstrapped estimates. The grade inflation and value-added measures used in estimating these correlations are constructed without shrinkage.

Table 5: Separate Regressions of High School Outcomes on One Teacher Measure

Panel A: LAUSD	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.055***	-0.031***	-0.008***	-0.006**	-0.010***	-11.930***
	(0.008)	(0.003)	(0.001)	(0.002)	(0.001)	(2.793)
Passing GI	-0.046***	-0.024***	-0.010***	-0.002	-0.007***	-11.614***
	(0.008)	(0.003)	(0.001)	(0.001)	(0.001)	(3.003)
Cog. VA	0.122***	0.062***	0.002	0.010**	0.032***	26.649***
	(0.011)	(0.003)	(0.001)	(0.003)	(0.004)	(3.498)
Noncog. VA	0.008	0.017***	-0.006***	0.011***	0.014***	0.552
	(0.007)	(0.003)	(0.001)	(0.002)	(0.002)	(1.604)
Outcome Mean	0.115	0.235	0.106	0.603	0.405	1,368.568
Observations	199,038.	215,559.	411,275.	326,975.	323,226.	173,195.
Panel B: Maryland	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.002	-0.013***	-0.003***	-0.001	-0.004+	-1.036
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(1.717)
Passing GI	-0.003	-0.004	-0.005***	0.002+	0.002	-2.477
	(0.004)	(0.003)	(0.001)	(0.001)	(0.003)	(2.268)
Cog. VA	0.018***	0.036***	0.001**	0.001**	0.007***	-2.346
	(0.005)	(0.003)	(0.000)	(0.001)	(0.002)	(1.693)
Noncog. VA	0.009**	0.016***	-0.003***	0.007***	0.002	-5.085***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(1.753)
Outcome Mean	-0.19	0.04	0.04	0.91	0.68	1239.73
Observations	109,382	242,524	607,437	607,437	607,437	127,241

Notes: This table presents estimated coefficients from regressions of the relevant outcome (column) on the relevant teacher measure (row) and our main vector of controls. Thus, each *cell* reports an estimate from a different regression. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Teacher Grade Inflation and Value-Added on High School Outcomes

Panel A: LAUSD	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.024***	-0.021***	0.002	-0.008***	-0.005+	-1.570
	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)	(1.883)
Passing GI	-0.001	0.003	-0.012***	0.005+	0.003	-3.562+
	(0.006)	(0.003)	(0.002)	(0.003)	(0.002)	(1.994)
Cog. VA	0.118***	0.058***	0.000	0.007**	0.031***	26.094***
	(0.011)	(0.002)	(0.001)	(0.003)	(0.003)	(3.136)
Noncog. VA	-0.004	0.012***	-0.006***	0.011***	0.011***	1.678+
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.991)
Outcome Mean	0.02	0.09	0.13	0.55	0.34	1336.44
Observations	347,368	382,121	736,569	635,552	594,421	173,783
R^2	0.532	0.664	0.165	0.264	0.366	0.739
Panel B: Maryland	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.002	-0.008**	-0.001**	-0.001**	-0.005**	-0.640
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.785)
Passing GI	-0.003	0.001	-0.004***	0.002**	0.005	-2.368
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(2.407)
Cog. VA	0.017***	0.034***	0.001+	0.001	0.007***	-2.332
	(0.005)	(0.003)	(0.000)	(0.000)	(0.002)	(1.678)
Noncog. VA	0.007	0.013***	-0.003***	0.007***	0.002	-5.000***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(1.750)
Outcome Mean	-0.19	0.04	0.04	0.91	0.68	1239.73
Observations	109,382	242,524	607,437	607,437	607,437	127,241
R^2	0.367	0.590	0.154	0.219	0.262	0.758

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects of Teacher Grade Inflation and Value-Added on College and Career Outcomes in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI	-0.006***	-0.005***	0.000	-0.002	-0.004***	-0.002**	-55.9***	-144.8***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(12.0)	(44.2)
Passing GI	0.001	-0.000	-0.002+	-0.002	0.001+	0.000	39.7***	4.1
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(11.6)	(42.3)
Cog. VA	0.002**	0.001	-0.003***	0.001	-0.002***	-0.002**	-55.1***	-39.5
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(12.0)	(34.6)
Noncog. VA	0.007***	0.005***	-0.002**	-0.000	0.003***	0.003***	54.6***	80.6**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(10.3)	(36.7)
Outcome Mean	0.67	0.60	0.27	0.41	0.69	0.63	4,981.6	17,544.3
Observations	801,898	801,898	677,364	393,143	801,898	393,143	801,898	393,143
R^2	0.281	0.295	0.239	0.333	0.038	0.048	0.077	0.042

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Dynamic Effects of Grade Inflation on College Enrollment in Maryland

Panel A: Enrolled in Associate's X Years Post Expected HS Graduation								
	$X = 1$	$X = 2$	$X = 3$	$X = 4$	$X = 5$	$X = 6$	$X = 7$	$X = 8$
Mean GI	-0.005***	-0.005***	-0.003***	-0.002***	-0.001**	-0.001***	-0.001**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Passing GI	0.003***	0.003***	0.001**	0.001**	0.001+	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Outcome Mean	0.26	0.22	0.16	0.10	0.07	0.05	0.04	0.03
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.030	0.030	0.022	0.015	0.010	0.009	0.007	0.008
Panel B: Enrolled in Bachelor's X Years Post Expected HS Graduation								
	$X = 1$	$X = 2$	$X = 3$	$X = 4$	$X = 5$	$X = 6$	$X = 7$	$X = 8$
Mean GI	-0.000	-0.001	-0.002**	-0.002**	-0.003***	-0.002***	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Passing GI	-0.002**	-0.002**	-0.001+	-0.001	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Outcome Mean	0.22	0.22	0.25	0.25	0.13	0.07	0.05	0.03
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.142	0.146	0.156	0.146	0.032	0.012	0.008	0.007
Panel C: Enrolled in Any College X Years Post Expected HS Graduation								
	$X = 1$	$X = 2$	$X = 3$	$X = 4$	$X = 5$	$X = 6$	$X = 7$	$X = 8$
Mean GI	-0.006***	-0.005***	-0.006***	-0.005***	-0.005***	-0.003***	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Passing GI	0.001	-0.000	0.000	-0.000	0.001	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Outcome Mean	0.67	0.60	0.52	0.49	0.30	0.16	0.12	0.10
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.281	0.295	0.266	0.271	0.069	0.025	0.018	0.014

Notes: This table presents estimates from regressions of being enrolled in the relevant postsecondary degree program (panel), measured X years (column) after expected high school graduation, on mean grade inflation and passing grade inflation as well as cognitive value-added, noncognitive value-added, and our main vector of controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. The timing of enrollment is measured relative to expected high school graduation as of 9^{th} grade; for example, "1 year post HS" refers to 5 years after we see the student in 9^{th} grade. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Dynamic Effects of Grade Inflation on College Graduation in Maryland

Panel A: Graduated with Associate's X Years Post Expected HS Graduation			
	$X = 4$	$X = 5$	$X = 6$
Mean GI	-0.001***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Passing GI	0.001	0.001+	0.001
	(0.000)	(0.001)	(0.001)
Outcome Mean	0.08	0.09	0.10
Observations	677,364	557,660	393,143
R^2	0.030	0.031	0.033
Panel B: Graduated with Bachelor's X Years Post Expected HS Graduation			
	$X = 4$	$X = 5$	$X = 6$
Mean GI	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)
Passing GI	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)
Outcome Mean	0.21	0.31	0.34
Observations	677,364	557,660	393,143
R^2	0.242	0.319	0.334
Panel C: Graduated from Any College X Years Post Expected HS Graduation			
	$X = 4$	$X = 5$	$X = 6$
Mean GI	0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
Passing GI	-0.002+	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Outcome Mean	0.27	0.37	0.41
Observations	677,364	557,660	393,143
R^2	0.239	0.318	0.333

Notes: This table presents estimates from regressions of graduating from the relevant postsecondary degree program (panel), measured X years (column) after expected high school graduation, on mean grade inflation and passing grade inflation as well as cognitive value-added, noncognitive value-added, and our main vector of controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. The timing of college graduation is measured relative to expected high school graduation as of 9th grade; for example, "1 year post HS" refers to 5 years after we see the student in 9th grade. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Dynamic Effects of Grade Inflation on Labor Market Outcomes in Maryland

	$X=1$	$X=2$	$X=3$	$X=4$	$X=5$	$X=6$	$X=7$	$X=8$
Panel A: Unconditional Winz. Earnings X Years Post Expected HS Graduation								
Mean GI	-55.9***	-77.6***	-96.4***	-85.6***	-57.9	-144.8***	-97.6	-23.3
	(12.0)	(16.4)	(21.8)	(24.7)	(29.7)	(44.2)	(51.4)	(88.3)
Passing GI	39.7***	53.2***	73.5***	50.6	23.1	4.1	-7.3	25.9
	(11.6)	(18.4)	(21.2)	(27.0)	(30.4)	(42.3)	(51.9)	(102.8)
Outcome Mean	4,981.6	7,169.0	8,589.9	10,118.1	14,369.5	17,544.3	20,037.7	22,374.6
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.077	0.077	0.075	0.067	0.037	0.042	0.044	0.038
Panel B: Employed 2 or More Quarters X Years Post Expected HS Graduation	$X=1$	$X=2$	$X=3$	$X=4$	$X=5$	$X=6$	$X=7$	$X=8$
Mean GI	-0.005***	-0.004***	-0.004***	-0.003***	-0.001	-0.002**	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Passing GI	0.002***	0.002***	0.003***	0.002+	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Outcome Mean	0.41	0.46	0.46	0.46	0.49	0.49	0.49	0.49
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.059	0.063	0.067	0.063	0.044	0.046	0.050	0.048
Panel C: Any Employment X Years Post Expected HS Graduation	$X=1$	$X=2$	$X=3$	$X=4$	$X=5$	$X=6$	$X=7$	$X=8$
Mean GI	-0.004***	-0.003***	-0.003***	-0.002***	-0.001	-0.002**	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Passing GI	0.001+	0.001	0.001**	0.001	0.000	0.000	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Outcome Mean	0.69	0.70	0.68	0.65	0.65	0.63	0.61	0.60
Observations	801,898	801,898	758,909	677,364	557,660	393,143	233,962	111,888
R^2	0.038	0.035	0.038	0.042	0.041	0.048	0.053	0.054

Notes: This table presents estimates from regressions of labor market outcomes (panel), measured X years (column) after expected high school graduation, on mean grade inflation and passing grade inflation as well as cognitive value-added, noncognitive value-added, and our main vector of controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. Earnings are winsorized at the 99^{th} percentile. The timing of college graduation is measured relative to expected high school graduation as of 9^{th} grade; for example, "1 year post HS" refers to 5 years after we see the student in 9^{th} grade. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effects of Teacher Measures Among Low- and High-Achieving Students in the LAUSD

Panel A: Below Median	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.029***	-0.026***	-0.003	-0.009***	0.001	-0.571
	(0.006)	(0.005)	(0.003)	(0.003)	(0.002)	(1.717)
Passing GI	0.001	0.005	-0.014***	0.008***	0.000	-4.695**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(1.931)
Outcome Mean	-0.29	-0.25	0.21	0.46	0.16	1227.57
Observations	135,623	151,835	288,046	214,389	223,206	52,809
R^2	0.342	0.537	0.161	0.245	0.237	0.654
Panel B: Above Median	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.026***	-0.018***	0.003**	-0.003	-0.006	-1.171
	(0.007)	(0.004)	(0.001)	(0.003)	(0.004)	(1.976)
Passing GI	0.001	0.005	-0.010***	0.001	0.004	-3.364+
	(0.008)	(0.003)	(0.001)	(0.003)	(0.003)	(2.011)
Outcome Mean	0.33	0.48	0.04	0.78	0.55	1386.70
Observations	159,603	169,901	284,952	233,193	222,682	160,202
R^2	0.578	0.682	0.077	0.146	0.276	0.753
Panel C: P-values from Tests of Coefficient Equality	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.7799	0.1538	0.0271	0.0982	0.0561	0.7324
Passing GI	0.9302	0.9401	0.0987	0.0267	0.2657	0.3874

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. The sample is split into students whose 8th grade GPA is below and above median as a proxy for low- and high-achieving students. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. Panel C shows *p* values of tests for coefficient equality that were constructed using seemingly unrelated regressions. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Effects of Teacher Measures Among Low- and High-Achieving Students in Maryland

Panel A: Below Median	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.003	-0.008**	-0.004***	-0.001	-0.004+	-5.148***
	(0.005)	(0.004)	(0.001)	(0.001)	(0.003)	(1.598)
Passing GI	-0.004	0.001	-0.006**	0.004***	0.004	-0.133
	(0.005)	(0.004)	(0.002)	(0.001)	(0.004)	(2.002)
Outcome Mean	-0.34	-0.35	0.07	0.86	0.54	997.16
Observations	48,499	110,433	225,249	262,055	225,249	26,844
R^2	0.281	0.479	0.165	0.221	0.230	0.600

Panel B: Above Median	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.005	-0.006	-0.000	-0.000	-0.005**	1.327
	(0.006)	(0.005)	(0.000)	(0.001)	(0.002)	(1.898)
Passing GI	-0.001	0.001	-0.003+	0.001	0.007+	0.129
	(0.005)	(0.004)	(0.002)	(0.001)	(0.004)	(1.964)
Outcome Mean	0.08	0.41	0.01	0.96	0.81	1183.41
Observations	41,554	119,867	249,278	284,938	249,278	46,293
R^2	0.513	0.605	0.127	0.120	0.169	0.658

Panel C: P-values from Tests of Coefficient Equality	Future Test (math)	Future Test (ela)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.2218	0.5167	0.0004	0.2352	0.8694	0.0002
Passing GI	0.5850	0.9477	0.0305	0.0262	0.0562	0.8748

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. The sample is split into students whose 8$^{\text{th}}$ grade GPA is below and above median as a proxy for low- and high-achieving students. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. Panel C shows p values of tests for coefficient equality that were constructed using seemingly unrelated regressions. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

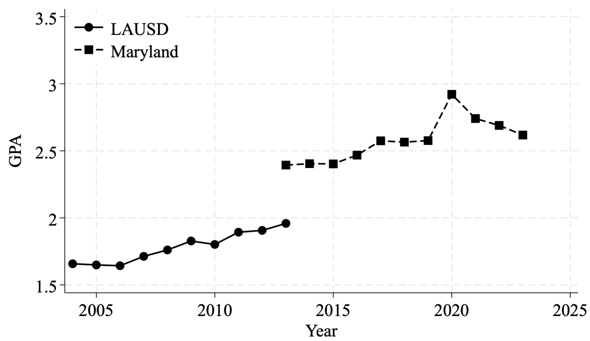
Table 13: Effects of Teacher Measures Among Low- and High-Achieving Students in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Panel A: Below Median								
Mean GI	-0.007***	-0.006***	-0.001	-0.002	-0.006***	-0.001	-66.5***	-110.0
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(21.1)	(93.3)
Passing GI	-0.000	-0.001	-0.001	-0.004***	0.003***	0.004+	43.0***	77.1
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(16.4)	(74.9)
Outcome Mean	0.51	0.43	0.13	0.24	0.70	0.66	6,013.8	18,415.2
Observations	262,055	262,055	204,420	72,859	225,249	55,173	225,249	55,173
R^2	0.249	0.248	0.145	0.245	0.036	0.042	0.053	0.046
Panel B: Above Median								
	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI	-0.002	-0.002+	-0.002	-0.002	-0.004***	-0.003	-49.6***	-163.7
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(19.1)	(115.5)
Passing GI	0.001	-0.000	-0.001	-0.002	0.001	-0.001	29.0	-16.2
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(20.3)	(85.1)
Outcome Mean	0.78	0.72	0.39	0.58	0.67	0.60	4,498.5	19,955.0
Observations	284,938	284,938	218,433	77,732	249,278	60,469	249,278	60,469
R^2	0.204	0.234	0.201	0.303	0.044	0.073	0.093	0.042
Panel C: P-values from Tests of Coefficient Equality								
	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI	0.0004	0.0093	0.4807	0.8349	0.3021	0.6583	0.5054	0.6900
Passing GI	0.3472	0.4639	0.7764	0.4036	0.2163	0.1048	0.5790	0.3805

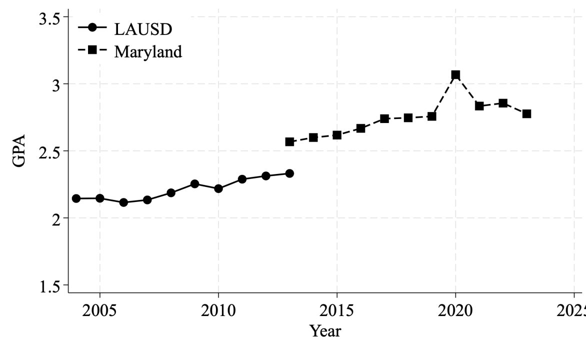
Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. The sample is split into students whose 8^{th} grade GPA is below and above median as a proxy for low- and high-achieving students. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. Panel C shows p values of tests for coefficient equality that were constructed using seemingly unrelated regressions. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Average GPA over Time by Subject

(a) Math



(b) ELA



Notes: This figure plots average math and English GPA over time for students in our LAUSD and Maryland samples. The data from the LAUSD span 2004 to 2013 and the data from Maryland span 2013 to 2023. GPA is measured on a 0 to 4 scale (e.g., A = 4.0, B = 3.0).

Table A.1: Correlations with Alternative Grading Leniency Measures

Panel A: LAUSD	Fig. and Luc. Measure	Gersh. et. al. Measure	Mean GI	Passing GI	Cog. VA	Noncog. VA
Figlio and Lucas Measure	1.0000	0.9988	-0.6734	-0.5261	0.7567	-0.0121
Gershenson et. al. Measure	.	1.0000	-0.6677	-0.5095	0.7586	-0.0060
Panel B: Maryland	Fig. and Luc. Measure	Gersh. et. al. Measure	Mean GI	Passing GI	Cog. VA	Noncog. VA
Figlio and Lucas Measure	1.0000	0.9991	-0.5752	-0.1771	0.6690	-0.1647
Gershenson et. al. Measure	.	1.0000	-0.5730	-0.1688	0.6722	-0.1665

Notes: Within-teacher-year correlations are estimated using an error correction procedure based on randomly splitting the data within classroom. Reported correlations are the average across 200 bootstrapped estimates. The teacher measures used in estimating these correlations are constructed without shrinkage. Alternative grading leniency measures are constructed as in Figlio and Lucas (2004) and Gershenson et al. (2022).

Table A.2: Actual Outcome Variable Forecast Bias Tests of Alternative Grading Leniency Measures

	Math		English	
Panel A: LAUSD	Figlio and Lucas	Gershenson et. al.	Figlio and Lucas	Gershenson et. al.
Corresponding Measure	0.94	0.97	0.90	0.90
	(0.02)	(0.02)	(0.01)	(0.01)
Observations	462,370	462,794	530,667	530,646
Panel B: Maryland	Figlio and Lucas	Gershenson et. al.	Figlio and Lucas	Gershenson et. al.
Corresponding Measure	0.98	0.98	0.96	0.96
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	209,927	209,927	252,480	252,480

Notes: This table presents results from the forecast bias test which regresses actual outcome variables on value-added estimates applied to the measures from Figlio and Lucas (2004) and Gershenson et al. (2022). We regress jackknifed, empirical Bayes estimates of the two measures on standardized test scores. Standard errors are clustered at the school level.

Table A.3: Predicted Outcome Forecast Bias Tests of Alternative Grading Leniency Measures

Panel A: Figlio and Lucas Measure, LAUSD	Math			English		
	Standard Controls	Predictors	Both	Standard Controls	Predictors	Both
Figlio and Lucas Measure	0.45	0.47	0.58	0.67	0.59	0.68
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Observations	462,370	195,453	195,453	530,667	239,621	239,621
Panel B: Figlio and Lucas Measure, Maryland	Math			English		
	Standard Controls	Predictors	Both	Standard Controls	Predictors	Both
Figlio and Lucas Measure	0.44	0.27	0.38	0.56	0.30	0.59
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Observations	209,927	46,749	46,749	252,480	65,723	65,723
Panel C: Gershenson et. al. Measure, LAUSD	Math			English		
	Standard Controls	Predictors	Both	Standard Controls	Predictors	Both
Gershenson et. al. Measure	0.46	0.48	0.58	0.66	0.58	0.67
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Observations	462,794	195,618	195,618	530,646	239,138	239,138
Panel D: Gershenson et. al. Measure, Maryland	Math			English		
	Standard Controls	Predictors	Both	Standard Controls	Predictors	Both
Gershenson et. al. Measure	0.42	0.25	0.35	0.54	0.29	0.59
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)
Observations	209,927	46,749	46,749	252,480	65,723	65,723

Notes: This table presents results from the forecast bias test which regresses outcomes predicted by a set of omitted observables applied to the measures from Figlio and Lucas (2004) and Gershenson et al. (2022). We regress jackknifed, empirical Bayes estimates of grade inflation measures on outcomes predicted by a set of variables omitted from the controls used to estimate the measures. Columns labeled "Standard Controls" use all controls used in our standard estimation procedure for other teacher measures as omitted variables. Columns labeled "Predictors" use twice-lagged values of standardized test scores, math, English and total GPA, fraction days absent and suspensions in LA, and the same twice-lagged values in Maryland but excluding test scores and including race, gender and FRPL status. Columns labeled "Both" use both standard controls and predictors. Standard errors are clustered at the school level.

Table A.4: Separate Regressions of College and Career Outcomes in Maryland on One Teacher Measure

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Log Conditional Earnings		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years	1 year	6 years
Mean GI	-0.006***	-0.005***	0.000	-0.003***	-0.004***	-0.002**	-0.003	-0.007**	-36.8***	-179.5***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(12.7)	(49.5)
Passing GI	-0.001	-0.002+	-0.002+	-0.003***	-0.000	-0.000	0.005**	-0.003	15.6	-81.4**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(12.0)	(39.8)
Cog. VA	0.002***	0.001	-0.003***	-0.000	-0.001	-0.001	-0.008***	-0.002	-41.1***	-24.6
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(13.9)	(46.1)
Noncog. VA	0.007***	0.006***	-0.001	0.001	0.003***	0.002+	0.008***	0.006+	57.8***	38.4
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(10.9)	(48.3)
Outcome Mean	0.65	0.58	0.27	0.40	0.68	0.63	8.32	9.79	5,080.5	17,972.8
Observations	607,437	607,437	482,906	239,853	607,437	239,853	415,784	150,302	607,437	239,853

Notes: This table presents estimated coefficients from regressions of the relevant outcome (column) on the relevant teacher measure (row) and our main vector of controls. Thus, each *cell* reports an estimate from a different regression. The outcomes in this table are only available in the Maryland data, not in LAUSD. The timing of enrollment is measured relative to expected high school graduation as of 9th grade; for example, "1 year post HS" refers to 5 years after we see the student in 9th grade. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Effects of Teacher Measures on Additional Outcomes in the LAUSD

	Future Held Back	Future Frac. Days Absent	Future Suspension	Graduate On Time	Don't Graduate	Leave Dataset Next Year	Took PSAT	PSAT Score
Mean GI	0.003+	0.001***	0.002**	-0.007+	0.011***	0.002	-0.004	-0.400**
	(0.002)	(0.000)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.170)
Passing GI	-0.005***	-0.001+	0.000	0.004	-0.009***	-0.004***	0.002	0.226
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.187)
Cog. VA	0.001	0.000	-0.001	0.006+	0.000	-0.000	0.014***	2.369***
	(0.001)	(0.000)	(0.000)	(0.003)	(0.002)	(0.001)	(0.004)	(0.325)
Noncog. VA	-0.012***	-0.002***	-0.005***	0.012***	-0.013***	0.001**	-0.003	0.254***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.087)
Outcome Mean	0.13	0.08	0.05	0.46	0.35	0.08	0.40	110.88
Observations	564,281	650,115	677,125	726,005	518,858	736,569	504,062	238,368
R^2	0.134	0.303	0.057	0.256	0.310	0.085	0.352	0.730

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Effects of Teacher Measures on Additional Outcomes in Maryland

	Future Held Back	Future Frac. Days Absent	Future Suspension	Graduate On Time	Took PSAT	PSAT Score	Took SAT or ACT	Cond. Log Earnings 1 Year Post HS	Cond. Log Earnings 6 Years Post HS
Mean GI	0.002***	0.001***	0.002***	-0.002**	-0.003	-0.031	-0.006***	-0.008***	-0.007+
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.140)	(0.002)	(0.003)	(0.004)
Passing GI	-0.001	-0.000	-0.000	0.003**	-0.000	-0.221	0.006**	0.008***	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.145)	(0.003)	(0.002)	(0.004)
Cog. VA	-0.001+	-0.000	-0.000	0.000	-0.004**	0.157	0.006***	-0.009***	-0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.106)	(0.002)	(0.003)	(0.003)
Noncog. VA	-0.004***	-0.001***	-0.004***	0.008***	-0.001	-0.686***	0.003	0.009***	0.007+
	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.139)	(0.002)	(0.002)	(0.004)
Outcome Mean	0.04	0.08	0.05	0.85	0.40	128.04	0.72	8.32	9.79
Observations	575,917	575,821	575,917	607,437	607,437	135,523	607,437	415,784	150,302
R^2	0.098	0.378	0.072	0.320	0.606	0.735	0.274	0.085	0.049

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effects of Measures of Teacher Grade Inflation and Value-Added with Demographic Controls on High School Outcomes in Maryland

	Future Test (math)	Future Test (ela)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.004	-0.006	-0.002***	-0.001	-0.005**	-0.820
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.815)
Passing GI	-0.004	0.001	-0.005***	0.003**	0.005	-2.890
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(2.186)
Cog. VA	0.018***	0.033***	0.001	0.001**	0.005***	-1.831
	(0.005)	(0.003)	(0.000)	(0.001)	(0.002)	(1.663)
Noncog. VA	0.001	0.013***	-0.003***	0.007***	0.001	-4.665**
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.845)
Outcome Mean	-0.18	0.04	0.04	0.91	0.69	1242.81
Observations	88,506	196,526	473,894	473,894	473,894	97,792
R^2	0.379	0.603	0.159	0.219	0.269	0.774

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative measures of mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added. The alternative measures are created using additional demographic controls available only in Maryland: race, sex, and use of Free and Reduced Price Lunch. The regressions also include those additional controls along with our standard controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Effects of Teacher Grade Inflation and Value-Added with Demographic Controls on College and Career Outcomes in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI	-0.006***	-0.005***	0.001	-0.001	-0.004***	-0.002	-67.6***	-155.3**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.5)	(64.1)
Passing GI	0.001	0.000	-0.002+	-0.002	0.001	0.000	30.9**	-21.8
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(14.0)	(49.6)
Cog. VA	0.001	-0.001	-0.004***	-0.001	-0.001+	-0.002+	-40.3***	-68.4
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.9)	(49.3)
Noncog. VA	0.008***	0.007***	-0.001	0.001	0.003***	-0.000	54.7***	-23.2
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(12.7)	(53.5)
Outcome Mean	0.66	0.59	0.27	0.41	0.68	0.63	5,039.5	18,002.5
Observations	473,894	473,894	374,988	185,029	473,894	185,029	473,894	185,029
R^2	0.299	0.310	0.245	0.346	0.047	0.056	0.085	0.044

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative measures of mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added. The alternative measures are created using additional demographic controls available only in Maryland: race, sex, and use of Free and Reduced Price Lunch. The regressions also include those additional controls along with our standard controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effects of Teacher Grade Inflation Estimated Flexibly on High School Outcomes

Panel A: LAUSD	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.027***	-0.021***	0.001	-0.007**	-0.005+	-2.158
	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)	(1.776)
Passing GI	-0.003	0.002	-0.013***	0.006**	0.002	-3.551+
	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(1.825)
Cog. VA	0.096***	0.055***	-0.003+	0.014***	0.031***	23.483***
	(0.008)	(0.002)	(0.001)	(0.002)	(0.002)	(3.077)
Noncog. VA	-0.002	0.011***	-0.006***	0.010***	0.010***	1.739+
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.966)
Outcome Mean	0.02	0.09	0.13	0.55	0.34	1336.44
Observations	347,368	382,121	736,569	635,552	594,421	173,783
R^2	0.553	0.669	0.167	0.270	0.369	0.748
Panel B: Maryland	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	0.001	-0.006	-0.002***	-0.000	-0.005**	-2.405
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.819)
Passing GI	-0.002	0.001	-0.004***	0.002+	0.005	-1.988
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(2.139)
Cog. VA	0.016***	0.034***	0.001	0.001**	0.005***	-1.164
	(0.005)	(0.003)	(0.000)	(0.001)	(0.002)	(1.718)
Noncog. VA	0.005	0.012***	-0.002***	0.005***	0.000	0.539
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.740)
Outcome Mean	-0.18	0.05	0.04	0.91	0.69	1244.51
Observations	91,662	204,424	492,865	492,865	492,865	101,267
R^2	0.384	0.603	0.162	0.219	0.263	0.772

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative mean grade inflation and alternative passing grade inflation measures, as well as cognitive value-added, noncognitive value-added, and main vector of controls. These alternative measures of grade inflation were constructed in the same way as our preferred measures, but added cubic polynomials of lagged test scores. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Effects of Teacher Grade Inflation Estimated Flexibly on College and Career Outcomes in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI, No Test	-0.004***	-0.004***	-0.000	-0.002+	-0.002**	-0.001	-35.6***	-92.6
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.0)	(62.6)
Passing GI, No Test	0.001	0.000	-0.001	-0.002	-0.000	-0.001	13.6	-35.4
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.3)	(48.9)
Cog. VA	0.001	-0.001	-0.004***	-0.001	-0.001	-0.002	-39.0***	-57.8
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.6)	(49.2)
Noncog. VA	0.006***	0.006***	0.002**	0.002+	0.001	-0.002+	24.3**	-90.8
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(11.7)	(49.6)
Outcome Mean	0.66	0.59	0.27	0.41	0.68	0.63	5,032.4	17,917.4
Observations	492,865	492,865	389,308	191,156	492,865	191,156	492,865	191,156
R^2	0.288	0.299	0.239	0.339	0.041	0.056	0.080	0.042

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative mean grade inflation and alternative passing grade inflation measures, as well as cognitive value-added, noncognitive value-added, and main vector of controls. These alternative measures of grade inflation were constructed in the same way as our preferred measures, but added cubic polynomials of lagged test scores. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Effects of Subject-Specific Teacher Measures on High School Outcomes in the LAUSD

	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI (math)	-0.046***	-0.022***	0.000	-0.013***	-0.009**	-1.130
	(0.010)	(0.005)	(0.003)	(0.004)	(0.004)	(2.369)
Mean GI (English)	-0.005	-0.011***	0.003	-0.004	0.001	0.678
	(0.008)	(0.004)	(0.002)	(0.003)	(0.004)	(2.132)
Passing GI (math)	0.011	0.007	-0.011***	0.008**	0.003	-2.458
	(0.009)	(0.005)	(0.003)	(0.004)	(0.003)	(1.961)
Passing GI (English)	-0.001	-0.006	-0.012***	0.004	-0.001	-6.940**
	(0.009)	(0.005)	(0.002)	(0.004)	(0.004)	(2.645)
Cog. VA (math)	0.126***	0.017***	0.002+	-0.005	0.011***	21.297***
	(0.013)	(0.003)	(0.001)	(0.003)	(0.004)	(2.861)
Cog. VA (English)	0.058***	0.066***	-0.002	0.016***	0.033***	19.497***
	(0.008)	(0.003)	(0.001)	(0.002)	(0.002)	(3.285)
Noncog. VA (math)	-0.005	0.005***	-0.003***	0.006***	0.008***	-0.357
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.643)
Noncog. VA (English)	0.004	0.009***	-0.004***	0.006***	0.005***	0.517
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(1.241)
Outcome Mean	0.11	0.23	0.11	0.60	0.41	1368.58
Observations	199,038	215,559	411,275	326,975	323,226	173,195
R^2	0.564	0.679	0.160	0.274	0.379	0.746

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Effects of Subject-Specific Teacher Measures on High School Outcomes in Maryland

	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI (math)	0.004	-0.008	-0.001	-0.001	-0.003	0.001
	(0.008)	(0.005)	(0.001)	(0.001)	(0.003)	(2.616)
Mean GI (ela)	-0.001	-0.002	-0.002**	-0.000	-0.007**	0.382
	(0.007)	(0.007)	(0.001)	(0.001)	(0.003)	(2.610)
Passing GI (math)	-0.010	-0.003	-0.007***	0.004**	0.002	-7.384+
	(0.012)	(0.007)	(0.002)	(0.002)	(0.005)	(4.308)
Passing GI (ela)	-0.011	0.007	-0.009	0.002	0.024+	-1.689
	(0.015)	(0.013)	(0.006)	(0.004)	(0.012)	(7.261)
Cog. VA (math)	0.003	0.036***	-0.000	0.003**	0.007+	16.403***
	(0.011)	(0.007)	(0.001)	(0.001)	(0.004)	(3.822)
Cog. VA (ela)	0.034***	0.043***	0.002***	-0.001	0.008**	-13.387***
	(0.006)	(0.006)	(0.001)	(0.001)	(0.003)	(1.969)
Noncog. VA (math)	0.003	0.011**	-0.003***	0.004***	-0.001	-3.321+
	(0.006)	(0.004)	(0.001)	(0.001)	(0.003)	(1.970)
Noncog. VA (ela)	0.013**	0.001	-0.001	0.004***	0.001	-3.451
	(0.006)	(0.004)	(0.001)	(0.001)	(0.003)	(2.219)
Outcome Mean	-0.18	0.05	0.03	0.91	0.70	1215.64
Observations	63,997	129,242	326,872	326,872	326,872	68,669
R^2	0.386	0.580	0.149	0.203	0.258	0.753

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Effects of Subject-Specific Teacher Measures on College and Career Outcomes in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Log Conditional Earnings		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years	1 year	6 years
Mean GI (math)	-0.005***	-0.002	0.001	0.000	-0.006***	-0.005**	-0.009+	0.007	-82.7***	-111.1
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.007)	(25.6)	(107.5)
Mean GI (ela)	-0.006***	-0.007***	0.001	-0.002	-0.002+	-0.001	-0.007	-0.010	-33.9	-179.2**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.006)	(20.7)	(81.5)
Passing GI (math)	0.000	-0.003	-0.005**	-0.007**	0.003+	0.003	0.014**	-0.005	83.9***	-65.4
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.010)	(30.7)	(125.7)
Passing GI (ela)	0.005	0.006	-0.001	-0.003	0.002	-0.003	0.016+	-0.019	29.6	-143.5
	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.009)	(0.014)	(42.3)	(246.9)
Cog. VA (math)	-0.002	-0.004+	-0.003	-0.003	-0.005**	-0.007***	-0.001	-0.005	-21.6	-236.1**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.007)	(0.008)	(35.2)	(111.5)
Cog. VA (English)	0.002**	0.002	-0.004***	0.000	-0.002	0.000	-0.019***	-0.001	-94.9***	46.1
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.006)	(16.8)	(80.2)
Noncog. VA (math)	0.005***	0.005***	-0.000	-0.000	0.003***	0.001	0.009***	0.004	53.2***	-17.2
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(14.0)	(65.0)
Noncog. VA (English)	0.005***	0.004***	-0.001	0.000	0.000	0.002	0.001	0.003	11.5	68.5
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(16.5)	(68.2)
Outcome Mean	0.66	0.59	0.26	0.40	0.69	0.63	8.33	9.79	5,170.6	18,170.7
Observations	326,872	326,872	260,327	126,869	326,872	126,869	226,462	80,211	326,872	126,869
R^2	0.271	0.285	0.230	0.329	0.034	0.048	0.082	0.049	0.074	0.041

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean grade inflation, passing grade inflation, cognitive value-added, and noncognitive value-added, as well as our main vector of controls. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Correlations between Preferred and No Test Grade Inflation Measures

Panel A: LAUSD	Mean GI, No Test	Passing GI, No Test	Mean GI	Passing GI	Cog. VA	Noncog. VA
Mean GI, No Test	1.0000	0.8573	0.8926	0.7837	-0.2353	0.2413
Passing GI, No Test	.	1.0000	0.7558	0.8983	-0.1763	0.2576
Panel B: Maryland	Mean GI, No Test	Passing GI, No Test	Mean GI	Passing GI	Cog. VA	Noncog. VA
Mean GI, No Test	1.0000	0.3540	0.9769	0.3627	-0.1032	0.0945
Passing GI, No Test	.	1.0000	0.3338	0.9967	0.0033	0.0478

Notes: Within-teacher-year correlations are estimated using an error correction procedure based on randomly splitting the data within classroom. Reported correlations are the average across 200 bootstrapped estimates. No test grade inflation measures were constructed the same as our preferred grade inflation measures except we do not control for contemporaneous test scores. The grade inflation measures used in estimating these correlations are constructed without shrinkage.

Table A.15: Effects of No Test Teacher Grade Inflation and Value-Added on High School Outcomes

Panel A: LAUSD	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI, No Test	-0.019***	-0.025***	0.003	-0.009***	-0.007***	-2.182
	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)	(2.010)
Passing GI, No Test	-0.002	0.005	-0.013***	0.007**	0.004	-2.843
	(0.006)	(0.004)	(0.002)	(0.003)	(0.002)	(1.929)
Cog. VA	0.122***	0.060***	0.001	0.008***	0.031***	26.672***
	(0.011)	(0.002)	(0.001)	(0.003)	(0.003)	(3.255)
Noncog. VA	-0.004	0.012***	-0.006***	0.011***	0.011***	1.679+
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(1.005)
Outcome Mean	0.02	0.09	0.13	0.55	0.34	1336.44
Observations	347,368	382,121	736,569	635,552	594,421	173,783
R^2	0.532	0.664	0.165	0.264	0.366	0.739
Panel B: Maryland	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI, No Test	-0.008	-0.008**	-0.002***	-0.002***	-0.006***	-0.527
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(1.898)
Passing GI, No Test	0.004	-0.001	-0.007***	0.005***	0.005	-13.324***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(4.523)
Cog. VA	0.017***	0.035***	0.001**	0.001+	0.007***	-2.264
	(0.005)	(0.003)	(0.000)	(0.000)	(0.002)	(1.650)
Noncog. VA	0.007	0.013***	-0.003***	0.006***	0.001	-4.470***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(1.701)
Outcome Mean	-0.19	0.04	0.04	0.91	0.68	1239.73
Observations	109,382	242,524	607,437	607,437	607,437	127,241
R^2	0.367	0.590	0.155	0.219	0.262	0.759

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative mean grade inflation and alternative passing grade inflation measures, as well as cognitive value-added, noncognitive value-added, and main vector of controls. These alternative measures of grade inflation were constructed in the same way as our preferred measures, but excluding contemporaneous test scores. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Effects of No Test Teacher Grade Inflation and Value-Added on College and Career Outcomes in Maryland

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI, No Test	-0.007***	-0.006***	0.001	-0.003	-0.005***	-0.003**	-57.9***	-156.5***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(15.7)	(56.6)
Passing GI, No Test	0.004***	0.001	-0.004***	-0.006***	0.003***	0.003**	52.7***	-7.7
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(16.5)	(50.7)
Cog. VA	0.002**	0.001	-0.003***	-0.000	-0.001	-0.002	-45.1***	-29.5
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(13.8)	(45.8)
Noncog. VA	0.007***	0.006***	-0.000	0.001	0.003***	0.002+	58.7***	43.9
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(11.0)	(48.3)
Outcome Mean	0.65	0.58	0.27	0.40	0.68	0.63	5,080.5	17,972.8
Observations	607,437	607,437	482,906	239,853	607,437	239,853	607,437	239,853
R^2	0.284	0.296	0.234	0.334	0.037	0.049	0.075	0.041

Notes: This table presents estimates from regressions of the relevant outcome (column) on alternative mean grade inflation and alternative passing grade inflation measures, as well as cognitive value-added, noncognitive value-added, and main vector of controls. These alternative measures of grade inflation were constructed in the same way as our preferred measures, but excluding contemporaneous test scores. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Effects of Grade Inflation on High School Outcomes in Algebra Courses

Panel A: LAUSD	Future Test (math)	Future Test (ela)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.026***	-0.017***	-0.004	-0.002	-0.002	-5.236***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.002)	(1.897)
Passing GI	-0.008	-0.001	-0.014***	0.001	0.002	2.476
	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)	(1.909)
Cog. VA	0.060***	0.021***	-0.006**	0.004+	0.012***	7.251***
	(0.007)	(0.004)	(0.002)	(0.002)	(0.003)	(1.541)
Noncog. VA	0.004	0.008**	0.002	0.007***	0.004**	1.616
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(1.113)
Outcome Mean	-0.28	-0.26	0.22	0.38	0.16	1175.73
Observations	137,862	149,519	235,070	162,920	184,139	37,461
R^2	0.335	0.535	0.155	0.251	0.204	0.592

Panel B: Maryland	Future Test (math)	Future Test (English)	Held Back	Graduate in 5 Years	Took SAT	SAT Score
Mean GI	-0.027**	-0.032***	-0.006***	-0.002	-0.001	-12.915**
	(0.011)	(0.008)	(0.002)	(0.002)	(0.005)	(5.862)
Passing GI	0.009	0.011	-0.001	0.004+	0.003	-5.703
	(0.015)	(0.009)	(0.003)	(0.002)	(0.004)	(6.643)
Cog. VA	0.024	0.021**	-0.001	0.002	0.006	-20.584+
	(0.015)	(0.008)	(0.002)	(0.003)	(0.006)	(10.556)
Noncog. VA	0.005	0.008	-0.003**	0.003**	-0.006+	4.855
	(0.007)	(0.005)	(0.001)	(0.001)	(0.003)	(3.201)
Outcome Mean	-0.17	-0.35	0.09	0.81	0.48	868.34
Observations	22,552	74,495	142,270	123,648	142,242	1,104
R^2	0.294	0.552	0.176	0.203	0.228	0.581

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean and passing grade inflation, value-added measures, and the main vector of controls, constructed for a subsample of courses. The subsample includes only students in Algebra 1 courses. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's Algebra 1 instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Effects of Grade Inflation on College and Career Outcomes in Algebra Courses

	Enrolled in Postsecondary		Graduated from Postsecondary		Employed		Unconditional Winz. Earnings	
	1 year	2 years	4 years	6 years	1 year	6 years	1 year	6 years
Mean GI	-0.013***	-0.010***	-0.002	0.002	-0.009***	-0.002	-107.2**	-182.2
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.007)	(41.8)	(271.0)
Passing GI	0.007**	0.001	-0.001	-0.004	0.001	-0.006	-9.8	-88.2
	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.007)	(47.5)	(324.8)
Cog. VA	0.004	0.003	-0.000	0.007	0.002	-0.024**	-41.8	-800.4**
	(0.003)	(0.003)	(0.004)	(0.009)	(0.004)	(0.010)	(53.2)	(394.8)
Noncog. VA	0.000	-0.000	-0.003	0.000	0.002	-0.002	30.2	-109.2
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.004)	(22.4)	(159.3)
Outcome Mean	0.45	0.37	0.12	0.18	0.69	0.66	6,569.8	17,044.0
Observations	123,648	102,458	57,239	19,261	123,648	19,261	125,601	19,261
R^2	0.220	0.207	0.149	0.224	0.035	0.042	0.049	0.052

Notes: This table presents estimates from regressions of the relevant outcome (column) on mean and passing grade inflation, value-added measures, and the main vector of controls, constructed for a subsample of courses. The subsample includes only students in Algebra 1 courses. The outcomes in this table are only available in the Maryland data, not in LAUSD. For this student-year level analysis, value-added and grade inflation are measured as averages across the student's math and English instructors in each year. The controls include school, grade, and year fixed effects, ELL, and previous year values of math test score, English test score, total GPA, fraction of days absent, suspension, and held back. Standard errors are clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.