Human Capital Formation During Childhood and Adolescence: Evidence from School Quality and Postsecondary Success in California

JOB MARKET PAPER

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Abstract

This paper investigates the role of school quality in human capital formation. Using the universe of public school students in California, I estimate elementary, middle, and high school quality using a value added methodology that accounts for the fact that students sort to schools on observable characteristics. I then determine the impact of school quality on future K–12 and postsecondary outcomes. I find that high school quality has the largest impact on postsecondary enrollment, while elementary and middle school quality play a larger role in college readiness. Thus, early human capital investments are important for future postsecondary success, but the unique timing of the college decision process allows for later human capital investments to also play a significant role. In addition, there is within-school heterogeneity in value added by socioeconomic status. While schools provide equal value added on test scores to low- and high-socioeconomic status students by the time they reach high school, they provide less value added on postsecondary enrollment to low-socioeconomic status students.

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1 Introduction

The timing of human capital investments is an important determinant of their efficacy. Because early human capital investments both augment and improve the productivity of later human capital investments (Cunha et al., 2006), early interventions have been shown to be the most effective and efficient (Heckman, Krueger and Friedman, 2003; Heckman, 2006; Doyle et al., 2009). The effects of early human capital interventions tend to fade out rather quickly (Currie and Thomas, 1995, 1999; Bitler, Hoynes and Domina, 2014), however, although they often reappear when examining long-run outcomes (Garces, Thomas and Currie, 2002; Ludwig and Miller, 2007; Deming, 2009; Duncan and Magnuson, 2013). Dynamic complementarities may play a large role in the persistence of early interventions, as evidence suggests that the benefits of a pre-school program were larger when followed by access to better-funded public K–12 schools (Johnson and Jackson, 2017).

Nevertheless, human capital formation and interventions that occur after pre-school have also been shown to have lasting effects on long-run outcomes. Elementary and middle school students assigned a high-quality teacher have a lower likelihood of having children as teenagers, a higher likelihood of attending college, and earn higher salaries. The effects are substantial, as replacing a teacher in the bottom five percent of the distribution with an average teacher would increase the present value of students' lifetime income by about $250,000 (Chetty, Friedman and Rockoff, 2014*b*).[1] Later interventions can matter too. Students given college advising and mentoring as late as their senior year of high school have been shown to be more likely to enroll and persist in college (Carrell and Sacerdote, 2013; Barr and Castleman, 2017; Castleman and Goodman, 2018). This includes interventions that occur after high school, as professors have been shown to affect college persistence and choice of major (Carrell, Page and West, 2010), and an evaluation of a vocationally-focused education and training program for youths between the ages of 16 and 24 showed that program participation increased educational attainment, reduced criminal activity, and increased earnings for several postprogram years (Schochet, Burghardt and McConnell, 2008).

One large contributor to human capital formation is schools. While teachers can have important impacts on the long-run outcomes of their students[2], there are other factors within a school that may determine student outcomes as well, such as principals (Clark, Martorell and Rockoff, 2009; Horng, Klasik and Loeb, 2010; Loeb, Kalogrides and Horng, 2010; Grissom and Loeb, 2011; Ladd, 2011; Béteille, Kalogrides and

[1] Despite these lasting effects, the persistence of teacher-induced learning is low from grade to grade (Jacob, Lefgren and Sims, 2010). This paradox may be explained by the fact that teachers may have long-term effects that are not initially apparent on contemporaneous test scores but manifest themselves in the future (Carrell and West, 2010).

[2] There is a large literature on teacher quality. See, for example, Rockoff (2004); Hanushek et al. (2005); Jacob and Lefgren (2005); Rivkin, Hanushek and Kain (2005); Hanushek and Rivkin (2006); Kane, Rockoff and Staiger (2008); Kane and Staiger (2008); Ishii and Rivkin (2009); Rothstein (2009); Carrell and West (2010); Corcoran (2010); Hanushek and Rivkin (2010); Jacob, Lefgren and Sims (2010); Rothstein (2010); Hanushek (2011); Kinsler (2012); Bacher-Hicks, Kane and Staiger (2014); Bitler et al. (2014); Chetty, Friedman and Rockoff (2014*a*,*b*); Staiger and Kane (2014); Guarino et al. (2015); De Vlieger, Jacob and Stange (2017); Chetty, Friedman and Rockoff (2017); Rothstein (2017).

Loeb, 2012; Branch, Hanushek and Rivkin, 2012; Loeb, Kalogrides and Béteille, 2012; Gates et al., 2014; Grissom, Blissett and Mitani, 2018), counselors (Carrell and Carrell, 2006; Reback, 2010; Carrell and Hoekstra, 2014), curricula (Altonji, 1995; Yu and Mocan, 2018), and spending (Hanushek, 1989; Hanushek, Rivkin and Taylor, 1996; Hanushek, 1997, 2003; Martorell, Stange and McFarlin Jr, 2016; Lafortune, Rothstein and Schanzenbach, 2018). Additionally, high-quality teachers may sort to schools based on school or location characteristics (Lankford, Loeb and Wyckoff, 2002; Ladd, 2011), further reinforcing the role that schools play in providing high-quality instruction to their students. Moreover, while parents have some say over which teachers teach their children, they have a much larger say over which school their children attend. Thus, it is important to understand how broad measures of school quality affect longer-run outcomes.

While there have been many studies that show that parents value schools with high ratings and average test scores (Bogart and Cromwell, 1997; Black, 1999; Downes and Zabel, 2002; Figlio and Lucas, 2004; Bayer, Ferreira and McMillan, 2007; Hastings and Weinstein, 2008; Burgess et al., 2015), others show that these measures of school demand are uncorrelated with estimates of how much schools *improve* student performance (Hayes and Taylor, 1996; Kane et al., 2003; Cullen, Jacob and Levitt, 2006; Kane, Riegg and Staiger, 2006; Hastings, Kane and Staiger, 2009; Imberman and Lovenheim, 2016; Abdulkadiroğlu et al., 2017). Recent studies that attempt to recover the causal effect of attending a particular school primarily fall into two groups: studies that use randomized admission lotteries or regression discontinuities to account for the potential issue of student selection into schools (Abdulkadiroğlu et al., 2011; Dobbie and Fryer Jr, 2011; Pop-Eleches and Urquiola, 2013; Deming et al., 2014; Deming, 2014; Dobbie and Fryer Jr, 2015; Angrist et al., 2016; Dobbie and Fryer Jr, 2016; Angrist et al., 2017) and models that account for selection on observables by extending existing value added methodologies from teachers to schools (Kurlaender, Carrell and Jackson, 2016; Abdulkadiroğlu et al., 2017; Hubbard, 2017). Each strategy has its strengths and weaknesses. Lotteries provide unbiased estimates from random assignment but are limited to schools with admission lotteries, such as charter schools. Value added methods often have larger samples and increased generalizability given the assumption that the models adequately control for selection holds.

Despite this growing literature, there are at least two unanswered questions when it comes to the impact of attending a high quality school. First, it is not clear *when* attending a high quality school matters most. Although there are studies on school quality at the elementary, middle, and high school level, this is the first paper to my knowledge that compares the long-run effects of school quality across school levels. I explore how school quality affects both the extensive and intensive margins of postsecondary outcomes. The extensive margin, postsecondary enrollment, may be affected by aspects of a school's quality beyond the cognitive skills the school teaches (such as non-cognitive skills, information on the college application process, or a culture of college attendance). The intensive margin, measured by a student's college readiness and persistence,

is much more likely to be affected by cognitive skills alone. Schools that play a large role in one margin may not necessarily impact the other, as each school level may impart different skills throughout a student's education.

Second, there is little research on *for whom* attending a high quality school matters. For the most part, the previous literature on school and teacher quality assumes that good schools and teachers are beneficial for *all* students. By reporting only a single measure for each school or teacher, these studies calculate the average effect of a school or teacher for all students. Although a measure of overall school quality is undoubtedly important, it is not necessarily informative to whether a school will be effective for a *specific type* of student. Average measures ignore the presence of within-school heterogeneity in quality for subgroups of students due to potential differences across schools in match quality. For example, students have been shown to perform better (Dee, 2004, 2007; Egalite, Kisida and Winters, 2015; Gershenson et al., 2017) and are less likely to be disciplined (Dee, 2005; Lindsay and Hart, 2017; Holt and Gershenson, 2017) when assigned to a same-race or same-sex teacher. Likewise, teachers report higher evaluations of students who share the same race or sex (Dee, 2005). Yet, surprisingly, there is a dearth of research on the student-school match[3], despite the fact that there is substantial heterogeneity in teacher characteristics and other inputs at the school level.

To fill these gaps, this paper uses the universe of California public school students linked to postsecondary records to investigate how elementary, middle, and high school quality impact the extensive and intensive margins of postsecondary enrollment. This paper also investigates whether these schools provide differing quality to their low-socioeconomic status (SES) students by allowing schools to have a heterogeneous quality for low- and high-SES students. To do so I calculate school quality by employing the value added with drift methodology, as in Chetty, Friedman and Rockoff (2014*a*), with schools. The drift methodology, which allows value added to change from year to year, is particularly suited to the school quality setting, as schools experience faculty and staff turnover that could lead to changes in quality from year to year. I estimate both how school value added on standardized test scores translates to postsecondary success as well as estimate a school's total value added on postsecondary enrollment directly, which includes both test score and non test score factors.

Results show that high school quality has the largest impact on the extensive margin of postsecondary enrollment. A one standard deviation increase in high school value added increases postsecondary enrollment by 2.2 percentage points (3.4%) and 4-year enrollment by 2.8 percentage points (10.3%). However, elementary and middle school quality have the largest effect on the intensive margin, such as persistence and the need

[3]To my knowledge, only two economics papers explore how value added may differ by subgroup. Carrell, Page and West (2010) find that female students assigned to female professors in STEM classes perform better and are more likely to obtain a STEM degree than their fellow female students who are assigned a male professor. Bau (2015) explores how private schools in Pakistan compete in horizontal quality when students respond differentially to match quality by socioeconomic status.

for remedial classes upon enrollment. A one standard deviation increase in elementary school value added increases persistence to year two at four-year colleges by 1.2 percentage points (1.4%). A one standard deviation increase in middle school value added reduces the need for English and math remediation by 2.2 percentage points (9.5%) and 3.2 percentage points (14%) respectively. Thus, results indicate that earlier grades give students the tools to succeed in college while high schools play the largest role in the postsecondary education decision process.

Importantly, my results show there is substantial heterogeneity in the value added that schools provide for low- and high-SES students. The gap in value added that schools provide on test scores between low- and high-SES students in elementary school is about the size of the gap in value added between attending an average quality school and a school that is 0.4 standard deviations below average. This gap shrinks in middle school, however, and is non-existent by the time students reach high school. The gap in value added that schools provide on postsecondary enrollment, however, does not converge between low- and high-SES students as they age. Elementary schools improve the postsecondary enrollment of low-SES students by 9 percentage points less than high-SES students, and this gap only shrinks to 4.2 percentage points by high school. Thus schools measured as providing equal value added to all subgroups of students on test scores may still be failing their disadvantaged students on measures of long-term success.

Finally, I correlate the value added estimates with observable school characteristics in order to determine which school inputs are correlated with school quality. Surprisingly, there appears to be little to no pattern to these inputs and my value added estimates. One exception is that having faculty that match the student body on demographic characteristics is correlated with higher school value added on test scores. Nevertheless, this effect does not persist to increases in postsecondary enrollment. I also find that funding for elementary school after-school programs is correlated with higher value added on postsecondary enrollment, thus, after-school supervision during students' earliest years may have important long-term effects.

This paper adds numerous important contributions to the literature on human capital broadly and education quality specifically. First, this is the first paper to study how school quality differentially contributes to human capital formation at various points during a student's educational career. Second, this paper is unique in that it links the universe of public school students in California, which has the largest public school population in the United States, to their postsecondary outcomes. California is a particularly relevant state in which to study postsecondary outcomes because California has a robust postsecondary infrastructure that includes two-year community colleges, teaching universities, and globally-ranked research universities. Third, this paper provides new insights on the relationship between K–12 school quality and measures of the intensive margin of postsecondary enrollment, which informs us about how schools contribute to college readiness. Finally, this paper provides some of the first evidence on whether schools differentially affect

postsecondary success for low-income students, which is especially relevant given the large enrollment gap by SES.

2 Data

My study uses data on the universe of public school students in the state of California. Standardized test score information comes from the California Standards Test (CST). Data from the CST spans the 2002-2003 to 2012-2013 school years[4] and tests students in English language arts (ELA) and math during grades 2-11. The data also include demographic information on each student, such as sex, race, economic disadvantage status, limited English proficiency status, and whether or not the student has a disability. State student IDs can be used to link students to prior test scores across time. Each cohort consists of about 475,000 students, which makes this the largest ever study on school quality.

Starting in the 7th grade, students have the option of taking different math assessments based on the math subject in which they are enrolled. This makes calculating school value added in math difficult, because scores are not directly comparable between the various math subjects within grades. Because all students take the same ELA exam in each grade, my primary analyses will investigate school quality on the ELA exam. In appendix section D I present results for math value added in elementary school, where there is a common test. Although studying differences between subjects for all levels of schooling would be ideal, Master, Loeb and Wyckoff (2017) show that ELA value added persists into future test scores on both ELA and math exams while math value added, on the other hand, only persists to future math scores. Thus, it is likely that teacher-induced learning on ELA subject matter imparts long-term skills that are broadly applicable, which may be important for postsecondary success.

Table 1 gives summary statistics for the CST data by school level for the test score value added sample and includes all the dependent and independent variables used in the value added analyses. Appendix Table 14 shows the limitations that are imposed in order to form the value added sample, which are similar to those made in the teacher value added literature. The vast majority of students in the CST data that cannot be included in the value added estimation are excluded because they lack prior test scores, although in high school an almost equal number of students are excluded because they attend alternative[5] high schools. For my analyses elementary school includes grade 4-5, middle school includes grades 6-8, and high school includes grades 9-11. I exclude grades 2-3 because they lack sufficient prior test scores in order to estimate value

[4] Due to the fact that I use test scores from two grades prior as a control variable, I only calculate value added estimates for the years 2004-2005 to 2012-2013.

[5] This includes schools in the following categories: Special Education Schools (Public), County Community, Youth Authority Facilities (CEA), Opportunity Schools, Juvenile Court Schools, Other County or District Programs, State Special Schools, Alternative Schools of Choice, Continuation High Schools, District Community Day Schools, Adult Education Centers, and Regional Occupational Center/Program (ROC/P).

added.[6]

Hispanics are the largest racial group in California, followed by whites, Asians, blacks, and other-race[7] students. Almost 60% of students in elementary school are socioeconomically disadvantaged[8], although this percentage declines slightly in more advanced school levels. Around a quarter of students are limited English proficient in elementary school, although this also declines as students age, likely due to the fact that students are reclassified as English proficient or higher dropout rates for limited English proficient students. About 4% of the sample has some type of disability. As is the case in other value added studies, the value added sample is positively selected on prior test scores, as they score anywhere from 0.06 to 0.14 standard deviations above average on their current test scores.[9] Appendix section A gives more information on the data.[10]

Postsecondary data comes from the NSC, the CSU system, and the CCC system. The NSC data includes enrollment and degree receipt data for the cohorts of students that graduated high school between the spring of 2010 and 2017, inclusive.[11] The NSC data includes all types of universities in the United States and, in particular, accounts for the lack of data from the University of California (UC), private California universities, and out of state universities that the CSU and CCC data do not account for. The CSU files include application and enrollment files from fall 2001 to spring 2017 and degree receipt files from fall 2001 to spring 2016. The CCC files include enrollment files from fall 1992 to spring 2017 and degree receipt files from fall 1992 to spring 2016. Appendix section B explains the details of the match between the K–12 and postsecondary data. Table 2 gives an overview of all of the datasets used in this paper.

3 School Value Added

3.1 Model

In this section I describe a model of student learning in order to better describe which factors contribute to a school's value added measure. Suppose that the outcome of a student i in grade g of school s in year t

[6]Prior test scores are necessary in order to obtain unbiased estimates when using value added methodologies (Kane and Staiger, 2008).

[7]The other category includes Native Americans and two or more races.

[8]Defined by the California Department of Education (CDE) as "a student neither of whose parents have received a high school diploma or a student who is eligible for the free or reduced-price lunch program, also known as the National School Lunch Program (NSLP)."

[9]Test scores are standardized to have mean zero and standard deviation one at the grade by year level on the entire population of students taking the CST.

[10]The value added sample differs from the overall population of students on a few demographic characteristics due to sample restrictions. The high school value added sample is 8% less likely to be male, 37% less likely to be black, 43% less likely to be limited English proficient, and 57% less likely to have a disability than the students who are excluded from the value added sample. Appendix Table 15 gives a comparison between the included and excluded students.

[11]The cohorts matched were actually spring 2009 to spring 2016 11th grade students, because we do not observe high school graduation data nor the students in 12th grade.

is determined according to equation (1), such that a student's endowment ι_i, contemporaneous learning ℓ_{ig}, prior learning ℓ_{ik} depreciated by a factor δ_k, and idiosyncratic school-level shocks θ_{st} all contribute. Assume that students take each grade only once, so that g and t are interchangeable within student.

$$z_{isgt} = \underbrace{\iota_i}_{\text{Endowment}} + \sum_{k=0}^{g-1} \underbrace{\delta_k \cdot \ell_{ik}}_{\text{Prior Learning}} + \underbrace{\underbrace{\ell_{ig}}_{\text{Learning}} + \underbrace{\theta_{st}}_{\text{Shocks}} + \underbrace{\varepsilon_{isgt}}_{\text{Noise}}}_{r_{isgt}} \tag{1}$$

Assume that the portion of outcome z_{isgt} that is due to learning is modeled by equation (2) such that teachers τ_{sgt} and other school factors ψ_{st} (such as principals, counselors, curricula, extracurricular activities, and peers) contribute to student learning.

$$\ell_{ig} = \underbrace{\tau_{sgt}}_{\text{Teachers}} + \underbrace{\psi_{st}}_{\text{School Factors}} \tag{2}$$

While other studies have investigated the impact of τ_{sgt} on long-run outcomes, studying school quality allows ψ_{st} to also have an impact. This may be particularly important when studying the effects of education on postsecondary enrollment, as high schools are much more likely to have counselors dedicated to the postsecondary decision process and some schools may have better resources on the application process, such as college fairs or mandatory SAT/ACT testing, than others.

Note that by regressing the test score in grade g on the test score in grade $g-1$ it is possible to control for ι_i and $\sum_{k=0}^{g-1} \delta_k \cdot \ell_{ik}$, the performance a student would achieve even in the absence of school input. This leaves us with the residual term r_{isgt}, which captures the portion of student performance that is not related to the student's prior achievement.

3.2 Methodology

To estimate ℓ_{ig}, I extend the value added methodology that allows for drift over time described in Chetty, Friedman and Rockoff (2014*a*) to the school level. The value added methodology accounts for the fact that schools receive students of varying backgrounds.[12] Hence, schools that receive only the lowest performing students should not be penalized for the fact that the students they receive will likely have lower outcomes on average. Instead, they should be evaluated on how much they improve the outcomes of those students, regardless of the students' prior achievement. Thus, a school that improves the test scores of the lowest-performing students would be determined to have a higher value added than a school that made no change to the test scores of the highest performing students, even though the latter school's students may perform

[12] Value added methodologies were first pioneered in estimating school and hospital quality (Willms and Raudenbush, 1989; McClellan and Staiger, 1999, 2000). Meyer (1997) and Everson (2017) provide some background on the methodology.

better on average.

A school's value added is calculated by first removing the portion of each student's test score that is due to non-school factors. To do so, I regress student test scores z_{isgt} on cubic polynomials in prior test scores $\boldsymbol{z}_{ig}$, demographic characteristics $\boldsymbol{X}_{it}$, and the number of students in a student's cohort (defined as school by grade by year) $\boldsymbol{W}_{sgt}$ as in equation (3). I also include grade fixed effects γ_g and year fixed effects ψ_t. The demographic characteristics $\boldsymbol{X}_{it}$ contain a linear term for age and fixed effects for sex, ethnicity[13], limited English proficiency, and disability status.

$$z_{isgt} = \boldsymbol{z}_{ig}\boldsymbol{\delta}_g + \boldsymbol{X}_{it}\boldsymbol{\beta}_X + \boldsymbol{W}_{sgt}\boldsymbol{\beta}_W + \gamma_g + \psi_t + r_{isgt} \tag{3}$$

Because there could be idiosyncratic shocks that are uncorrelated with school quality but influence the performance of all students within a school in each year, such as the proverbial dog barking outside of the school on the day of the test, the residual term r_{isgt} will contain school value added μ_{st}, idiosyncratic shocks θ_{st}, and a student-level error term ε_{isgt} as in equation (4).

$$r_{isgt} = \mu_{st} + \theta_{st} + \varepsilon_{isgt} \tag{4}$$

I average this residual to the school by year level. Assuming that students do not sort to schools on unobservable characteristics and that ε_{isgt} is a mean zero random error term, the student-level error terms will average to zero at the school by year level due to the fact that $\mathbf{E}[\varepsilon_{isgt}|st] = \mathbf{E}[\varepsilon_{isgt}] = 0$. However, because value added and idiosyncratic shocks are the same for all students at this level, the average residual will contain both school value added and the school-level idiosyncratic shock as in equation (5).

$$\bar{r}_{st} = \mu_{st} + \theta_{st} \tag{5}$$

In order to remove the idiosyncratic shocks and isolate only value added, I project the average residual in year t onto the residuals in all other years t' (jackknife projection) as in equation (6).

$$\bar{r}_{st} = \bar{\boldsymbol{r}}_{st'}\boldsymbol{\beta}_{\bar{r}t'} + \epsilon_{st} \tag{6}$$

Assuming that the school-level common shocks are uncorrelated across years ($\text{cov}(\theta_{st}\theta_{st'}) = 0$), the school-level common shocks are not correlated with school value added across years ($\text{cov}(\mu_{st}\theta_{st'}) = 0$), and school value added is correlated across years ($\text{cov}(\mu_{st}\mu_{st'}) \neq 0$), the jackknife projection will purge the value added estimate of the idiosyncratic shock but retain the school's persistent value added. The value added

[13] Asian, Hispanic, black, and other; white is omitted.

estimates that I use in this paper are the predicted values from equation (6), $\hat{\mu}_{st} = \bar{\boldsymbol{r}}_{st'}\hat{\boldsymbol{\beta}}_{\bar{r}t'}$. However, I rescale the estimates so that they have mean zero for each school level and subject combination, thus, schools with positive value added are above average and vice versa. This rescaling has no impact on the results to follow. I outline additional methodological details in appendix section C.

3.3 Results

Figure 1 shows the distributions of school value added. The standard deviation of school value added ranges from a low of 0.066 for high school ELA to a high of 0.134 for elementary school math. This tells us, for example, that a one standard deviation increase in high school value added increases the average ELA test score of its students by 6.6% of a standard deviation. The standard deviation for elementary school math is about twice the size of that for ELA, which is consistent with prior studies of school and teacher value added. The magnitudes are similar in size to those found for the distribution of school value added using charter school lotteries in Deming (2014) and for the distribution of teacher value added in Chetty, Friedman and Rockoff (2014*a*).[14]

The drift methodology, which allows a school's value added to change from year to year, is only an improvement over prior value added methodologies if a school's value added actually varies across time. To illustrate that this is true in practice, figure 2 shows the correlation between a school's value added estimate in year t and year t', where the horizontal axis gives the number of years between years t and t' and the vertical axis gives the correlation. Here we can see the importance of using the drift methodology. While a school's value added is highly correlated within a two-year window, the correlation begins to drop off as the number of years between estimates grows.

3.3.1 Validity Tests

There are three potential concerns with regards to the validity of the value added estimates. The first is that the estimates are picking up pure noise due to sampling error and small sample variability. This would be the case if test scores are sufficiently noisy that student-level residual test scores, ε_{isgt}, do not average out to zero at each school, even when schools have no effect on student performance. If this were the case, we would attribute value added to schools when we were in fact just observing sampling error.

In order to measure how much of the estimated variation in school value added is purely due to noise, I calculate school value added estimates after randomly assigning students to schools. I call these value added estimates permuted value added, as I permute the school assignment vector within a grade by year cell.

[14]The standard deviations are about a quarter of the size of those found for school value added in Angrist et al. (2017) and about half the size of those for teacher value added in Kane and Staiger (2008).

Figure 3 shows the distributions of permuted value added, and I plot the distributions on the same axes as figure 1 so that their variability can be directly compared. As can be seen, there is essentially no variation in school quality when students are randomly assigned to schools in this way. The largest permuted value added standard deviation relative to the actual value added standard deviation is 0.001 for high school, which is only 1.5% of the size of the actual value added standard deviation. This alleviates concerns that the value added estimates are merely an artifact of noisy test score measures or small sample variability.

Another concern is that the value added estimates are the incorrect size. Specifically, the issue is whether a one unit increase in school value added increases student test scores by one unit on average. In order to test for this issue, I run a bivariate regression of residualized test scores r_{isgt} on the school value added estimates μ_{st}, where the residualized test scores are calculated using equation (3). This calculates by how much a school's estimated value added actually increases the test scores of its students. We expect the coefficient to equal one, which would indicate that a one unit increase in school value added increases student test scores by one standard deviation on average. The first row of Table 3 provides this estimate along with its 95% confidence interval. While elementary school ELA and middle school have coefficients that are statistically different from one, all school levels have coefficient estimates that are economically indistinguishable from one. This gives evidence that the school value added estimates have the correctly-sized effect on student test scores. Furthermore, figure 4, which graphs the relationship between r_{isgt} and μ_{sdt} in 20 equally sized bins, shows that the value added estimates and test score residuals have an almost perfectly linear relationship throughout the value added distribution.

The final concern involves the potential sorting of students to schools based on unobserved ability. If students with high unobserved ability sort to specific schools, such that $cov(\varepsilon_{isgt}, \hat{\mu}_{st}) \neq 0$, then these schools' estimated value added will be higher than their true value added. However, this is only an issue if the sorting occurs on *unobserved* ability. There is no issue if students sort to schools on observed ability, because this will be controlled for with the inclusion of prior test scores. For example, if students with high test scores tend to attend the same schools, as occurs in practice, then we can still obtain unbiased estimates of school value added as long as prior test scores are included in the control vector. In fact, research comparing value added estimates to estimates obtained using random assignment to schools (Deming, 2014; Angrist et al., 2017) or teachers (Kane and Staiger, 2008) shows that once you control for prior test scores even the inclusion of demographic characteristics in the control vector is essentially irrelevant because prior test scores are a sufficient statistic for student ability. The primary threat to identification would be if students or parents *changed* their level of input into academic preparation between the student's prior grade and current grade and students sorted to schools based on this change in behavior.

The issue in determining to what degree students sort to schools on unobserved ability is that, by

definition, we have no measures of unobserved ability. However we can approximate unobserved ability using variables in our data that likely would be correlated with ability but that were not included as a control variable in equation (3). Given the available data, the best possible measure of unobserved student ability is an additional prior test score. Under the assumption that this omitted variable is the only component of ε_{isgt} that is correlated with student test scores, we can then obtain an estimate of $\frac{cov(\varepsilon_{isgt},\hat{\mu}_{st})}{var(\hat{\mu}_{st})}$. Chetty, Friedman and Rockoff (2014*a*) call this value forecast bias, which gives an estimate of what proportion of the variation in school value added is due to sorting on unobserved ability.

This value is estimated in the following steps. First I obtain the portion of contemporaneous test scores that projects onto three-grade prior test scores by adding three-grade prior test scores to equation (3). The projection is equal to the predicted value using only the test score from three grades prior. I then regress this projection on school value added. The second row of Table 3 provides the estimate of forecast bias along with its 95% confidence interval. Here we expect an estimate of zero, which would give evidence that there is no sorting of students to schools on unobservable characteristics. While all the estimates except for elementary school math are statistically different from zero, they are not economically significant as at most 3.9% of the variance in school value added is due to sorting on unobserved ability.[15] Figure 5 shows that this relationship holds throughout the distribution of school value added.

3.4 Average Test Scores

Given the evidence that the value added estimates truly measure school quality, one might wonder whether the average test scores at a school could provide the same information. After all, most parents interested in the academic performance of a school will look at the average level of test scores in the school in order to do so. Figure 6 plots a school's value added against the average test score of the students in the value added sample enrolled in that school. This figure shows that average test scores are not sufficient to predict the actual value added of a school. While average test scores and value added are positively related, as would be expected if value added causally impacted student test scores, average test scores do not account for the majority of the variation in school value added. In fact, the slope on the bivariate regression of value added on average test scores ranges from 0.059 to 0.141 depending on the school level and subject, which would imply that only up to 15% of a school's increase in test scores is due to the value added that that school provides. Furthermore, average test scores explain at most 24% of the variation in school value added. This indicates that a large portion of the average test scores at a school is simply due to the type of students that enroll as opposed to any benefits the school is actually providing. These results provide evidence as to why schools with high average test scores that are commonly in high demand by parents often do not improve

[15] Chetty, Friedman and Rockoff (2014*a*) estimate forecast bias of 2.2%.

the test scores of students who attend those schools (Beuermann and Jackson, 2018).

3.5 Student Correlations

Another common belief is that because school enrollment is largely dictated by neighborhoods, and households sort to neighborhoods (Nechyba, 2006), students are tracked into high or low quality schools throughout their education career. Figure 7 examines the degree to which this is true. Figure 7a shows that this belief is true if only looking at the average test score of students at the school. This figure plots the correlation of the average test score between a student's school levels. The horizontal axis gives a reference school level and the vertical axis gives the correlation between the reference school level and another school level. The average test score between consecutive school levels is quite high; 0.9 between elementary and middle school and 0.6 between middle and high school.

Figure 7b shows that this primarily reflects student sorting on average test scores, however, and that there is little tracking on causal school quality. This figure plots the correlation of value added between a student's school levels. Here the correlation is at most 0.2, and the correlation between middle and high school value added is almost zero. While this may be inefficient given the fact that human capital investments build off each other (Cunha et al., 2006), it is also equitable as it shows that schools do not necessarily perpetuate inequality for disdavantaged groups (Jennings et al., 2015) nor do advantaged students hoard educational resources and high growth schools (Hanselman and Fiel, 2017).

4 Long-Run Outcomes

While I've established the variability and validity of school value added on test scores, test scores have no inherent meaning unless they have lasting effects that eventually translate to labor market outcomes. I now test to see how school value added on test scores affects future K–12 outcomes, postsecondary enrollment, and postsecondary success. In order to do so, I run a regression of a student's outcome y_i on the student's school's value added as in equation (7). I run these regressions for each school level and subject separately.

$$y_i = \hat{\mu}_{st}\beta_\mu + \boldsymbol{z}_{ig}\boldsymbol{\delta}_g + \boldsymbol{X}_{it}\boldsymbol{\beta}_X + \boldsymbol{W}_{sgt}\boldsymbol{\beta}_W + \gamma_g + \psi_t + \nu_{isgt} \tag{7}$$

In all regressions I also include all of the control variables from equation (3) used in the estimation of school value added, as they will likely also contribute to postsecondary outcomes. I scale the value added estimates by the standard deviation of the estimated value added distribution, $\sigma_{\hat{\mu}_{st}}$, so that the coefficient β_μ can be interpreted as the effect of a one standard deviation increase in school value added. I cluster

bootstrap the standard errors clustering at the school level.

Because each student's postsecondary outcomes do not vary over time but their school's value added is allowed to drift over time, the regressions may contain multiple observations for a student with identical outcome values but differing school value added. For example, a student observed in 6th, 7th, and 8th grade who enrolls in college will have three distinct middle school value added estimates but will have a value of 1 for enrolling in college for all of those observations. In order to assure that all students contribute equal weight to each regression, I weight each observation by the inverse of the number of observations that a particular student contributes. Thus, a student observed in 6th, 7th, and 8th grade would have a weight of $\frac{1}{3}$ for each observation while a student observed only in 7th and 8th grade would have a weight of $\frac{1}{2}$. The regressions are therefore representative at the student level.

4.1 K–12 Outcomes

First I explore whether school value added impacts future K–12 performance. The outcomes I look at are ELA and math test scores one grade later, whether a student enrolled in a public school one grade later, and whether a student took the most advanced math subject in future grades. Table 4 shows that school value added persists to future test scores. In elementary school a one standard deviation increase in school value added increases test scores in the next grade by 8.8% and 12.6% of a standard deviation in ELA and math respectively. The effects for middle and high school are also similarly large, and the effect sizes at all school levels are close to the effect sizes on contemporaneous scores, which contrasts with evidence of fade out in other environments (Currie and Thomas, 1995, 1999; Bitler, Hoynes and Domina, 2014), although part of this may be due students remaining in the same school because school value added is highly correlated one year apart (as seen in figure 2). Interestingly, ELA value added has an even larger effect on future math scores than on future ELA scores, which suggests that school-induced learning on ELA exams may provide skills in other subjects. This is consistent with similar findings in Master, Loeb and Wyckoff (2017). School value added has an economically insignificant effect on remaining in the public school system, which combines the effect of transferring to a private school, dropout, and moving to another state. Finally, school value added has a positive impact on the math subject that students take, as students are more likely to take the hardest math subject when they first track to different math subjects in grade 7 as well as for their final math exam in grade 11.

4.2 Postsecondary Enrollment

Much more important, however, is the effect of school value added on postsecondary enrollment, because attending college has proven to be a worthwhile investment for both the average and marginal student (Oreopoulos and Petronijevic, 2013). Hoekstra (2009) finds that attending a flagship university increases the earnings of white men by 20%, while Zimmerman (2014) shows that admission to a 4-year university for the marginal student gives a wage premium of 22% and bachelor's degree receipt for the marginal admission increases wages by 90%. I define postsecondary enrollment as enrolling in any institution in the NSC data, a CSU, or a CCC within one year of high-school graduation. The sample consists solely of students who could potentially be matched to the NSC data, as students who did not enroll in a CSU or CCC and could not be potentially matched to the NSC data may still have enrolled in a postsecondary institution, such as a UC, but I would not observe this.

Table 6 shows the results from the regressions of postsecondary enrollment on school value added. I code two-year and four-year enrollment as mutually exclusive, so if students enroll in a both a two-year and four-year institution within a year of graduating high school (such as if they take a summer course at a community college) then I code them as only enrolling in a four-year institution. High school value added has the largest impact on postsecondary enrollment, as a one standard deviation increase in value added increases overall enrollment by 2.2 percentage points (3.4%). This is about 2.3 percentage points smaller than the effect of 11th grade grade value added on postsecondary enrollment found in Hubbard (2017). High school also has the largest impact on 4-year enrollment, with an effect of 2.8 percentage points (10.3%). Elementary and middle school value added have smaller, but still positive, effects on overall and 4-year enrollment, although elementary school ELA has a somewhat larger effect on 4-year enrollment than middle school. High value added elementary and high schools appear to induce students to enroll in a 4-year university instead of a 2-year college, which should provide a higher wage premium (Kane and Rouse, 1995).

As a robustness check, I run horse race regressions that include school value added from all levels of schooling for the subset of students that I observe in elementary, middle, and high school. These regressions take the form of equation 7, but instead of including the value added for a student's specific school level in the different years for which the student was enrolled in that level of school these regressions include the student's average value added estimate for elementary school ELA, elementary school math, middle school ELA, and high school ELA. I also use each student's average value of the other control variables to account for the fact that these values may change from grade to grade. This is a somewhat unique sample, because these are students that I observe for at least five consecutive grades. For this reason, the sample size is much smaller than that from the regressions in Table 6. Table 7 confirms that high school value added consistently

has the largest positive effect on postsecondary enrollment. This is likely due to the fact that high school enrollment is so close to the college decision process, which requires a concentrated effort at a very specific point in time.

We can also see a school's direct impact on postsecondary enrollment by replacing the dependent variable in equation (3) with an indicator for postsecondary enrollment. Because each student's enrollment outcome is invariant across grades, I only use observations from 5th grade for elementary school, 8th grade for middle school, and 11th grade for high school. Figure 8 shows the distributions of these postsecondary enrollment value added estimates. Again, we see that high school has the largest impact on postsecondary enrollment as it has the highest variance in value added. A high school that is one standard deviation above average in the value added that it provides on postsecondary enrollment increases the postsecondary enrollment of its students by 8.7 percentage points on average. Elementary and middle school have slightly smaller effects that are similar in size. Thus, the closer a student gets to enrolling in college the bigger the impact that the school they attend has on whether they actually end up enrolling. One notable difference between high school and the other school levels is the long, left tail of low-value added schools.

4.3 Conditional Outcomes

Next, I explore how school value added on test scores affects CSU and CCC outcomes that are conditional upon enrollment at one of those institutions. For CSU these outcomes include acceptance (conditional on application), remediation, STEM major, undecided major, persistence, degree receipt, and STEM degree receipt. For CCC these outcomes include remediation, persistence, transfer to a four-year university, degree receipt, and associate's degree receipt. I measure degree receipt within 6 years for 4-year degrees and within 3 years for 2-year degrees. The need for remedial classes is an inefficient use of resources, because students are paying college tuition for courses that they had the opportunity to take for free while enrolled in high school. STEM majors earn more than any other major with the exception of business (Arcidiacono, 2004; Melguizo and Wolniak, 2012; Kinsler and Pavan, 2015), and the premium has increased over time (Gemici and Wiswall, 2014). Both 2-year and 4-year degrees provide a wage premium for workers (Kane and Rouse, 1995).

The regressions for CSU outcomes are in Table 8. Interestingly, high value added schools decrease a student's likelihood of being accepted conditional on application, although the effect is extremely small. This is likely due to increases in CSU application on the extensive margin, where students have a low likelihood of acceptance, that dominate any increases in the probability of acceptance on the intensive margin. Encouragingly, high value added schools also reduce student's need for remedial classes upon enrolling at a

CSU. Middle school has the largest effect on the need for remediation followed by elementary school ELA, which has an even stronger effect on the need for math remediation than elementary school math value added. A middle school with value added one standard deviation above average decreases the need for remedial ELA and math classes by 2.2 percentage points (9.7%) and 3.2 percentage points (13.9%) respectively. School value added has no effect on whether students become a STEM major, but high value added schools do reduce the likelihood that students are undecided in their first year of college. This likely focuses course enrollment and reduces frivolous classes. Elementary school has the strongest effect on whether a student persists to their second or third year year of college, with middle school also having a significant effect. A one standard deviation increase in elementary school ELA value added increases the likelihood of persisting to year three by 1.4 percentage points (1.9%). However, school value added appears no have no effect on eventual degree receipt. Thus, the evidence suggests that while high school plays the largest role in whether students actually enroll in a postsecondary institution, as seen in section 4.2, elementary and middle schools develop the skills necessary for students to succeed in college.

The CCC outcomes are given in Table 9. Both elementary school ELA and math value added reduce the need for remedial CCC courses. A one standard deviation increase in elementary school math value added decreases the need for remedial math classes by 0.05 percentage points (2.6%). Persistence to year two at a community college is a somewhat complicated outcome, because the failure to persist could be a good outcome if the student transferred to a four-year university or bad outcome if the student dropped out of college altogether. In order to avoid this issue, I code a student as persisting to year two if they persisted to year two at a community college or transferred to a four-year university. I recode degree receipt and associate's degree receipt in the same way. High school has the largest impact on both persistence to year two and transfer to a four-year university. The impact of high school value added on transferring to a four-year university is particularly large, as a one standard deviation increase in high school value added increases the likelihood of transferring to a four-year university after enrolling at a CCC by 3 percentage points (8.3%). Thus, high schools not only have the largest impact on initial four-year enrollment but also have the largest impact on students enrolling in four-year universities indirectly. At all school levels attending a high value added school increases both degree receipt and associate's degree receipt, although this appears to be driven by transfer to a four-year university.

5 Value Added Heterogeneity

While I have shown that there is substantial variation in school value added on both test scores and post-secondary enrollment, the value added estimates that I have provided thus far calculate the average effect

of a school on its students. This ignores the possibility that schools may have heterogeneous effects on the different types of students that enroll. Of particular interest is whether schools have a differential impact on low-SES students, as these students perform worse than their more privileged counterparts on both short- and long-term academic outcomes. The low-/high-income test score gap has been increasing during the past 50 years (Reardon and Robinson, 2008; Reardon, 2011), as has the college-going gap (Bailey and Dynarski, 2011) and the elite college-going gap (Reardon, Baker and Klasik, 2012) even after accounting for academic ability (Belley and Lochner, 2007; Karen, 2002). Moreover, the low-/high-income test score gap only decreases slightly as students progress through school (Reardon, 2011).

These achievement gaps have important consequences. Students must compete on achievement in a variety of educational settings. Class rank, college admission, and scholarships are all competitions in which high-achieving students can reap large benefits, which could in turn prevent low-SES students from enrolling in college. More importantly, achievement gaps may contribute to the existence of poverty traps. Because cognitive gaps are highly predictive of wage gaps (Neal and Johnson, 1996; Bollinger, 2003; Carneiro, Heckman and Masterov, 2005), achievement gaps may perpetuate the cycle of poverty by ensuring that low-SES students obtain low-paying jobs and, in turn, have children who will suffer similar consequences from growing up in a low-income family. Schools that close the achievement gap for low-SES students could be a valuable mechanism for reducing poverty. I study this issue by allowing each school to have a separate value added estimate for its low-SES and high-SES students.

5.1 Simulation

A significant advantage of allowing a school's value added to vary by SES is that it corrects for the incorrect ranking of schools if the assumption of a homogeneous school effect is violated. In order to demonstrate this, I simulate a dataset of student observations. Let true value added for school s in year t be μ_{sLt} for type L students and μ_{sHt} for type H students. Let student test scores be generated according to the true model in equation (8), with school by type by year value added μ_{sdt}, school by year common shocks θ_{st}, and a noise term ε_{isdt} all contributing.

$$z_{isdt} = \mu_{sdt} + \theta_{st} + \varepsilon_{isdt} \tag{8}$$

For simplicity, let $\mu_{sdt} = \mu_{sd}\ \forall t$. Let there be four types of schools with equal probability, A, B, C, and D, with true school value added for type L and H distributed as μ_{sLt} and μ_{sHt} in columns 2 and 3 of Table 10. School A and school D are unambiguously the best and worst schools, respectively. School B is particularly effective with low-type students while school C is effective with high-type students. Notice that

on average schools provide more value added to high-type students.

Let N_{sLt} and N_{sHt} be the number of students of type L and H respectively. I assign each school a baseline value of N_{sLt} and N_{sHt} and allow the yearly population of low- and high-type students to fluctuate within a window of this baseline by multiplying N_{sLt} and N_{sHt} separately by an inflation term j_{sdt}. This allows for yearly variation in the proportion of students that are low-type within a school. The distributions for θ_{st}, ε_{isdt}, N_{sLt}, N_{sHt}, and j_{sdt}, as well as the number of schools and years, are given in Table 11.

Figure 9 plots the value added estimates obtained using the drift methodology in Chetty, Friedman and Rockoff (2014*a*) for the simulated data. Figures 9a, 9b, 9c, and 9d contain both the estimates under the assumption of a homogenous effect for all students and a heterogeneous effect for low- and high-type students for schools of type A, B, C, and D respectively. The horizontal axis plots the proportion of students who are low-type within the school. The horizontal red lines mark the true value added for each school. For each school type allowing for a heterogeneous value added effect produces estimates clustered around the true value regardless of what proportion of students are low-type. Imposing the assumption of a homogeneous value added effect, however, causes the value added estimate to fluctuate according the proportion of low-type students. While this issue is less pronounced when schools have similar value added for both low- and high-type students, such as schools A and D, the value added estimate can vary dramatically according to the proportion of low-type students when schools are more effective with a particular type of student, as with schools B and C.

Even worse, the assumption of homogeneous school value added can misrank schools when they are at the extreme end of the distribution of proportion low-type students. Figure 9e plots the homogeneous estimate for schools A and C. Despite the fact that school A is better than school C, since it is equally effective with high-type students but better with low-type students, its estimated effect is worse than school C if A enrolls a large proportion of low-type students and C enrolls a large proportion of high-type students. Allowing the schools to have heterogeneous effects, as in figure 9f, preserves the correct ranking of schools. This misranking illustrates the importance of studying within-school heterogeneity in value added.

5.2 Results

I assign students to low- or high-SES status based on whether they are defined as socioeconomically disadvantaged by the CDE. In order to get an idea of the income level of these students, figure 10 plots the distribution of total household income in 2017 dollars by socioeconomic disadvantage status from the Survey of Income and Program Participation (SIPP).[16] Economically disadvantaged students live in households

[16] I exclude observations with a total household income of greater than $250,000 from the figure but not the calculation of the median income, as there is a long, low-density right tail in each distribution.

with a median income of about $60,000, which is about $36,000 lower that the median income of students in households that are not economically disadvantaged. However, the peak of the income distribution for economically disadvantaged students occurs much lower at about $38,000.

Figure 11 plots the distribution of value added by SES on test scores. These value added estimates give the value added that a school provides to its low- and high-SES students specifically. In elementary school, schools provide less value added on average to low-SES students, although the standard deviation of value added for low- and high-SES students is about the same. The difference in average value added is about 3% of a standard deviation in both ELA and math. In middle and high school, however, schools provide similar value added to both low- and high SES students on average, but the standard deviation of value added for low-SES students is larger. At all school levels Kolmorgorov-Smirnoff tests for equality of distribution reject the hypothesis that the low- and high-SES value added distributions are equal, but by high school the difference in means between the low-SES and high-SES distributions is only significant at the 5% level.

While the difference in average value added on test scores for low- and high-SES students fully converges by the time students reach high school, this is not the case for postsecondary enrollment. Figure 12 plots the distribution of value added by SES on postsecondary enrollment. In general, the standard deviations of the value added estimates for low-SES students are fairly similar to those for high-SES students across all school levels. However, the mean of the value added distribution for low-SES students is statistically significantly lower than the mean for high-SES students at all school levels, which indicates that on average schools provide less value added on postsecondary enrollment to low-SES students than to high-SES students. High schools provide 4 percentage points less value added on postsecondary enrollment to low-SES students compared to high-SES students, and the difference is even larger in middle and elementary school. So while schools may be closing, or at least not exacerbating, the test score achievement gap by high school, they are not necessarily doing so for postsecondary enrollment. This is consistent with evidence that test scores are not necessarily the correct measure for determining whether schools perpetuate inequality (Jennings et al., 2015).

Next, I show that there is in fact within-school heterogeneity in value added. In figure 13 each point represents an observation for a school in a specific year, with the horizontal axis giving the school's value added for high-SES students and the vertical axis giving the school's value added for low-SES students. The figures indicate that while low- and high-SES value added are highly correlated, with the correlation ranging from 0.495 for elementary school to 0.792 for high school, there is also substantial within school heterogeneity in value added. The red line gives the points at which low- and high-SES value added are equal, and while the value added estimates trend parallel to this line, there is also substantial deviation. In particular, there are numerous schools in the bottom-right quadrant in which a school provides above average value added

for high-SES students and below average value added for low-SES students.

These findings show that focusing on a single measure of quality for each school may be misguided, as schools tend to provide less value added to low-SES students. Furthermore, because schools have a significant impact on whether students enroll in a postsecondary institution, the public school system could be a valuable asset for increasing the postsecondary outcomes of low-SES students. Given that students' income ranks are highly inherited by their parents' income rank (Chetty et al., 2014*a*) and that intergenerational mobility in the U.S. has stagnated in recent years (Chetty et al., 2014*b*) but that a college education of any level flattens the relationship between student income rank and parent income rank (Chetty et al., 2017), improving primary and secondary school quality may be an effective way to reduce poverty and increase intergenerational mobility.

6 Value Added Characteristics

6.1 School Characteristics

Finally, I explore what school characteristics are correlated with value added. While these regressions are not causal, they provide a description of what high value added schools have in common. This analysis may therefore provide clues of some effective characteristics that could be explored in a causal framework in future studies.

I run regressions of school value added on school-level inputs as in equation (9). I cluster bootstrap the standard errors clustering at the school level. In the first regression the school characteristics included in $\boldsymbol{X}_{st}$ are the number of full-time equivalent (FTE) teachers per student, FTE pupil services staff[17] per student, English-learner staff per student, proportion teachers with three years or less experience, proportion teachers with full credentials, proportion male teachers, proportion male students, and the interaction between the two, proportion minority[18] teachers, proportion minority students, and the interaction between the two, and total enrollment. In the second regression I include district expenditure data on instruction, pupil services (counselors, nurses, food service, etc.), ancillary services (before- and after-school programs), and general administration expenditures. I also include total enrollment to account for fixed costs.

$$\hat{\mu}_{st} = \boldsymbol{X}_{st}\boldsymbol{\beta} + \varepsilon_{st} \tag{9}$$

Table 12 shows the correlations between school value added and school characteristics. The left four

[17]This includes counselors, psychologists, librarian/library/media teachers, social workers, nurses, and speech/language/hearing specialists.

[18]Hispanic, black, Native American and two or more races.

columns give value added on test scores, while the right three columns give value added on postsecondary enrollment. There is no clear pattern of school characteristics that positively impact school value added at all levels. While student-teacher ratios have a positive impact on test school value added in elementary school, they have essentially no effect in middle and high school and have a negative impact on postsecondary enrollment value added. New teachers also have a surprisingly positive effect in elementary school, although they have the opposite effect on college-going. There is a similar story with fully-credentialed teachers, which goes against prior studies that show that teacher credentials have no effect on teacher value added (Kane, Rockoff and Staiger, 2008). The only strong consistent result is the interaction term between the proportion minority teachers and students on test score value added, which suggests that minorities may benefit from having teachers like them. However this positive effect does not extend to value added on postsecondary enrollment.

Table 13 gives correlations between school value added and district expenditures. Here we see little correlation between instruction expenditures and test score value added, although there is a significant relationship for value added on postsecondary enrollment. We also see that expenditures on ancillary services in elementary school are strongly correlated with value added on college-going, which suggests that after school programs in a student's earliest years may have long-lasting effects.

7 Conclusion

Human capital formation is a lifelong process, but because later investments build off of earlier investments the human capital accrued during childhood and adolescence may be particularly important. This paper studies the impact of school quality on human capital formation during these time periods. I estimate school value added in elementary, middle, and high school using the universe of public schools in California. I find that there is substantial variation in value added across schools, with the standard deviations of school value added ranging from 6.6% to 13.4% of a student test score standard deviation. I then link these value added estimates to data from the NSC, CSU, and CCC in order to study the impact of school value added on postsecondary outcomes. I find that high school value added has the largest effect on postsecondary enrollment, while elementary and middle school have stronger effects on college readiness. All school levels therefore contribute to human capital formation but in different ways.

I then explore whether schools provide differential value added to their low-SES students. I find that while the difference in average school test score value added for low-SES students is essentially the same as the average school test score value added for high-SES students by high school, all school levels provide less value added on postsecondary enrollment to their low-SES students. Furthermore, there is substantial

within-school heterogeneity in value added that is masked by examining averages, so some schools are more effective with students from a particular socioeconomic background.

While this paper shows that high value added schools have long-term effects on postsecondary outcomes, the question remains as to what comprises a high value added school. Prior research on school and teacher characteristics has been largely inconclusive as to what makes an effective school or teacher, and the correlational results that I present in this paper do not shed much light on the issue. Further research is needed in order to identify the replicable characteristics of high value added schools, as the evidence shows that these schools could permanently improve the lives of their students.

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A Data

Table 14 gives the number of observations in the CST data conditional on a set of restrictions implemented in order to form the value added sample. The rows are additive, such that the first row contains all observations, the second row imposes one restriction, the third row imposes two restrictions, etc. The first row denotes the total number of observations in the CST dataset. The second row keeps students who have information on test scores, as opposed to just demographic characteristics. The third row keeps only the first time that a student attempted a grade, and thus drops observations in which a student is repeating a grade. I impose this restriction because students repeating a grade are tested on material for which they have already been tested at least once. The fourth row keeps only students at "conventional" schools. This includes schools in the following categories defined by the CDE: Preschool, Elementary School (Public), Elementary School in 1 School District (Public), Intermediate/Middle Schools (Public), Junior High Schools (Public), K–12 Schools (Public), High Schools (Public), and High Schools in 1 School District (Public).[19] The fifth row drops any schools that enroll 10 students or fewer in a given year. The sixth row drops students who are missing a test score in the specific subject for which value added is calculated. The seventh row drops students who are missing any of the demographic controls. The eighth and ninth rows drop students who are missing test scores from one grade and two grades prior, respectively. This restriction is the cause of the vast majority of observations which are excluded from the value added estimates. The tenth row drops observations for which peer averages of the control variables could not be calculated. The eleventh row drops students if fewer than seven observations can be used to estimate value added for their school by year cell, which insures that all value added estimates are based on at least seven observations.

[19] This drops students in the following categories: Special Education Schools (Public), County Community, Youth Authority Facilities (CEA), Opportunity Schools, Juvenile Court Schools, Other County or District Programs, State Special Schools, Alternative Schools of Choice, Continuation High Schools, District Community Day Schools, Adult Education Centers, and Regional Occupational Center/Program (ROC/P).

Table 15 gives summary statistics for the students who are excluded from the value added sample. For comparison, the table also includes the summary statistics of the value added sample. Excluded students are more likely to be male and slightly more likely to be economically disadvantaged, black, two or more races, or American Indian. The most stark difference between included and excluded students, however, is in their likelihood of having a disability. Excluded students are over four times more likely to be disabled in elementary school and over twice as likely to be disabled in high school. This fact carries over to prior test scores, as excluded students are more likely to have lower prior achievement than students in the value added sample.

B CST to Postsecondary Match

Because we lack a unique student identifier common to both the CST and CSU/CCC data, such as a social security number, I match the CST data to the CSU/CCC data based on students' name, birth date, and sex. While there is no common unique student identifier, each dataset does have a unique student identifier specific to that dataset, which I will call the CST ID, CSU ID, and CCC ID, respectively. The match is implemented as a sieve, with progressively less strict matches in each sieve level.

For the CCC data, I match on first name, last name, birth date, and sex. I start by dropping all students in the CST and CCC datasets that are not uniquely identified by these variables, as for all intents and purposes they constitute the student's unique identifier. Denote the remaining observations as the *master CST* and *master CCC* datasets, respectively. I then match the master CST and master CCC datasets on first name, last name, birth date, and sex. Of those matched observations, I drop any observations that were missing data on any of the match variables. I then drop any students for whom their CST ID matched to multiple CCC IDs or their CCC ID matched to multiple CST IDs. The remaining matched observations I denote *sieve level 1*, which contains one observation per CST ID and CCC ID.

Next I remove all of the sieve level 1 observations from the master CST and master CCC datasets and repeat the steps above matching on first name, last name, and birth date. I denote this sieve level 2. For sieve level 3 I match on first three letters of first name, first three letters of last name, birth date, and sex. This is due to the fact that from 1993 to 2011 the CCC data only contains the first three letters of a student's first and last name. Finally for sieve level 4 I match on first three letters of first name, first three letters of last name, and birth date.

For the CSU data I implement the same matching procedure. Sieve level 1 matches on first name, last name, birth date, sex, and middle name. Sieve level 2 matches on first name, last name, birth date, and sex. Sieve level 3 matches on first name, last name, and birth date.

The NSC data was matched by the NSC using their proprietary match process. This process relies on a student's first name, middle initial, last name, and birth date.

Because of data limitations, the number of cohorts than can be matched to the postsecondary data varies by school level. Given the years available for the CST and CSU/CCC data, 6 cohorts from the elementary school value added sample, 9 cohorts from the middle school value added sample, and 11 cohorts from the high school value added sample could potentially be matched to the CSU/CCC data. For the NSC data 6 cohorts from the elementary school value added sample, 8 cohorts from the middle school value added sample, and 7 cohorts from the high school value added sample could potentially be matched to the NSC data.

C School Value Added Methodology

I follow the methodology described in Chetty, Friedman and Rockoff (2014*a*), implementing a few modifications in order to estimate school by year value added instead of teacher by year value added. A school's value added is calculated by first removing the portion of each student's test score that is due to non-school factors in order to isolate the portion of their test score that was influenced by the school. I regress student test scores z_{isgt} on a vector of prior test scores $\boldsymbol{z}_{ig}$, demographic characteristics $\boldsymbol{X}_{it}$, the number of students in a student's cohort $\boldsymbol{W}_{sgt}$, grade fixed effects γ_g, year fixed effects ψ_t, and a school fixed effect α_s as in equation (10).

The vector of prior test scores $\boldsymbol{z}_{ig}$ contains a cubic polynomial in one-grade-prior same-subject test score and a cubic polynomial in two-grade-prior same-subject test score. I allow the polynomials in prior scores to differ by grade by interacting the polynomials with grade fixed effects. The demographic characteristics $\boldsymbol{X}_{it}$ contain a linear term for age and fixed effects for sex, ethnicity, limited English proficiency, and disability status.

$$z_{isgt} = \boldsymbol{z}_{ig}\boldsymbol{\delta}_g + \boldsymbol{X}_{it}\boldsymbol{\beta}_X + \boldsymbol{W}_{sgt}\boldsymbol{\beta}_W + \gamma_g + \psi_t + \alpha_s \tag{10}$$

I then calculate residual test scores r_{isgt}, as shown in equation (11), that contain the component of student test scores that does not project onto observable student characteristics. Notice that while equation (10) contains a school fixed effect α_s, the residual test scores do not subtract off this predicted school fixed effect $\hat{\alpha}_s$.

Equation (10) contains a school fixed effect in order to account for potential correlation between school value added and student characteristics. If school value added is in fact correlated with the types of students

that enroll in the school, then the regression coefficients in equation (10) would be biased in the absence of a school fixed effect because the omitted variable of school quality would be correlated with both the dependent and independent variables. The residual r_{isgt} does not subtract the predicted school fixed effect, however, because doing so would leave us with a residual test score that no longer contained school value added.

$$r_{isgt} = z_{isgt} - (\boldsymbol{z}_{ig}\hat{\boldsymbol{\delta}}_g + \boldsymbol{X}_{it}\hat{\boldsymbol{\beta}}_X + \boldsymbol{W}_{sgt}\hat{\boldsymbol{\beta}}_W + \hat{\gamma}_g + \hat{\psi}_t) \tag{11}$$

It is helpful to decompose r_{isgt} into its corresponding components. Equation (12) shows that residual test scores are composed of school value added μ_{st}, common shocks θ_{st}, and an individual level error term ε_{isgt}.

$$r_{isgt} = \mu_{st} + \theta_{st} + \varepsilon_{isgt} \tag{12}$$

I then average residual test scores r_{isgt} to the school by year level as in equation (13). Substituting (12) into equation (13) gives us equation (14), and equation (15) follows under the assumption that $\mathbf{E}[\varepsilon_{isgt}|st] = \mathbf{E}[\varepsilon_{isgt}] = 0$.

$$\begin{aligned}
\bar{r}_{st} &= \frac{\sum_{i \in st} r_{isgt}}{N_{st}} && (13)\\
&= \frac{\sum_{i \in st}(\mu_{st} + \theta_{st} + \varepsilon_{isgt})}{N_{st}} && (14)\\
&= \mu_{st} + \theta_{st} && (15)
\end{aligned}$$

The issue is that there is no variation in the common shocks θ_{st} within each school by year cell, so the average residual test score contains both true school value added as well as a common shock that is unrelated to school quality. Under the assumption that common shocks are uncorrelated across time and value added is correlated across time, however, we can project the average residual in year t onto the average residuals from all other years from the same school in order to purge the common shocks.

Formally, if the assumptions in (16) hold,

$$\text{cov}(\theta_{st}\theta_{st'}) = 0, \qquad \text{cov}(\mu_{st}\theta_{st'}) = 0, \qquad \text{cov}(\mu_{st}\mu_{st'}) \neq 0 \qquad \forall t' \neq t \tag{16}$$

then we can project $\bar{r}_{st}$ onto $\bar{\boldsymbol{r}}_{st'}$ to recover μ_{st} following equation (17), where $\bar{\boldsymbol{r}}_{st'}$ is the vector of average

residuals $\bar{r}_{st'}$ $\forall t' \neq t$.

$$\bar{r}_{st} = \bar{\boldsymbol{r}}_{st'}\boldsymbol{\beta}_{\bar{r}t'} + \epsilon_{st} \tag{17}$$

If we have years $t = 1, \ldots, T$ then

$$\bar{\boldsymbol{r}}_{st'} = \begin{bmatrix} \bar{r}_{s1} & \bar{r}_{s2} & \ldots & \bar{r}_{st-1} & \bar{r}_{st+1} & \ldots & \bar{r}_{sT-1} & \bar{r}_{sT} \end{bmatrix} \tag{18}$$

and

$$\boldsymbol{\beta}_{\bar{r}t'} = \begin{bmatrix} \beta_{\bar{r}1} & \beta_{\bar{r}2} & \ldots & \beta_{\bar{r}t-1} & \beta_{\bar{r}t+1} & \ldots & \beta_{\bar{r}T-1} & \beta_{\bar{r}T} \end{bmatrix}' \tag{19}$$

However, there is a fundamental tradeoff between the number of independent variables and the number of observations that can be included in equation (17). For example, if the average residual from 5 years prior to year t is used, then a regression following (17) can only include schools that have at least 6 consecutive years of data. Some schools that close or open during the span of the dataset won't have this many observations, so they will be dropped from the regression. Thus, while including the average residual from 5 years prior to year t will increase the information that can be used to identify μ_{st}, it will decrease the number of observations used to identify $\beta_{\bar{r}t-1}$ to the subset of schools that have been open for at least 6 consecutive years. This subset will contain fewer observations than the number of observations that have a valid $\bar{r}_{st-1}$, as this only requires having 2 consecutive years of data. Thus, including $\bar{r}_{st-5}$ would essentially discard useful information in identifying $\boldsymbol{\beta}_{\bar{r}t-1}$ in order to identify $\boldsymbol{\beta}_{\bar{r}t-5}$.

Examining the coefficient vector $\boldsymbol{\beta}_{\bar{r}t'}$ is helpful in dealing with this issue. Solving equation (17) using ordinary least squares (OLS) provides us with the solution vector in (20).

$$\boldsymbol{\beta}_{\bar{r}t'} = (\bar{\boldsymbol{r}}'_{st'}\bar{\boldsymbol{r}}_{st'})^{-1}(\bar{\boldsymbol{r}}'_{st'}\bar{\boldsymbol{r}}_{st}) \tag{20}$$

First let's examine $(\bar{\boldsymbol{r}}'_{st'}\bar{\boldsymbol{r}}_{st'})^{-1}$. The resulting matrix is equal to (21).

$$\begin{bmatrix} \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{s2} & \dots & \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{st-1} & \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{st+1} & \dots & \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{s1}\bar{\boldsymbol{r}}_{sT} \\ \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{s2} & \dots & \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{st-1} & \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{st+1} & \dots & \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{s2}\bar{\boldsymbol{r}}_{sT} \\ \vdots & \vdots & \ddots & \vdots & \vdots & & \vdots & \vdots \\ \bar{\boldsymbol{r}}'_{st-1}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{st-1}\bar{\boldsymbol{r}}_{s2} & \dots & \ddots & & \dots & \bar{\boldsymbol{r}}'_{st-1}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{st-1}\bar{\boldsymbol{r}}_{sT} \\ \bar{\boldsymbol{r}}'_{st+1}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{st+1}\bar{\boldsymbol{r}}_{s2} & \dots & & \ddots & \dots & \bar{\boldsymbol{r}}'_{st+1}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{st+1}\bar{\boldsymbol{r}}_{sT} \\ \vdots & \vdots & & \vdots & \vdots & \ddots & \vdots & \vdots \\ \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{s2} & \dots & \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{st-1} & \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{st+1} & \dots & \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{sT-1}\bar{\boldsymbol{r}}_{sT} \\ \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{s1} & \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{s2} & \dots & \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{st-1} & \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{st+1} & \dots & \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{sT-1} & \bar{\boldsymbol{r}}'_{sT}\bar{\boldsymbol{r}}_{sT} \end{bmatrix}^{-1} \tag{21}$$

Under the stationarity assumptions in (22),

$$\mathbf{E}[\mu_{st}|t] = 0, \qquad \mathbf{E}[\theta_{st} + \varepsilon_{isgt}|t] = 0, \qquad \text{cov}(\mu_{st}\mu_{st+y}) = \sigma_{\mu y} \tag{22}$$

we have $\mathbf{E}[\bar{r}_{st}|t] = 0$, which therefore allows us to write the sums of squares $\bar{\boldsymbol{r}}'_{st}\bar{\boldsymbol{r}}_{st}$ as variances $\sigma^2_{\bar{r}_{st}}$ and the cross products $\bar{\boldsymbol{r}}'_{st}\bar{\boldsymbol{r}}_{st'}$ as covariances $cov(\bar{r}_{st}, \bar{r}_{st'})$. Furthermore, because we assume that the covariance between the average residual from any two years only depends on the number of years between them, we can rewrite $\sigma^2_{\bar{r}_{st}} = \sigma^2_{\bar{r}}$ and $cov(\bar{r}_{st}, \bar{r}_{st'}) = \sigma_{\bar{r}y}$, where $y \equiv |t - t'|$ indexes the number of years between t and t'. This simplifies the matrix in (21) further to (23).

$$\begin{bmatrix} \sigma^2_{\bar{r}} & \sigma_{\bar{r}1} & \dots & \sigma_{\bar{r}t-2} & \sigma_{\bar{r}t} & \dots & \sigma_{\bar{r}T-2} & \sigma_{\bar{r}T-1} \\ \sigma_{\bar{r}1} & \sigma^2_{\bar{r}} & \dots & \sigma_{\bar{r}t-3} & \sigma_{\bar{r}t-1} & \dots & \sigma_{\bar{r}T-3} & \sigma_{\bar{r}T-2} \\ \vdots & \vdots & \ddots & \vdots & \vdots & & \vdots & \vdots \\ \sigma_{\bar{r}t-2} & \sigma_{\bar{r}t-3} & \dots & \ddots & & \dots & \sigma_{\bar{r}T-t} & \sigma_{\bar{r}T-t+1} \\ \sigma_{\bar{r}t} & \sigma_{\bar{r}t-1} & \dots & & \ddots & \dots & \sigma_{\bar{r}T-t-2} & \sigma_{\bar{r}T-t-1} \\ \vdots & \vdots & & \vdots & \vdots & \ddots & \vdots & \vdots \\ \sigma_{\bar{r}T-2} & \sigma_{\bar{r}T-3} & \dots & \sigma_{\bar{r}T-t} & \sigma_{\bar{r}T-t-2} & \dots & \sigma^2_{\bar{r}} & \sigma_{\bar{r}1} \\ \sigma_{\bar{r}T-1} & \sigma_{\bar{r}T-2} & \dots & \sigma_{\bar{r}T-t+1} & \sigma_{\bar{r}T-t-1} & \dots & \sigma_{\bar{r}1} & \sigma^2_{\bar{r}} \end{bmatrix}^{-1} \tag{23}$$

Next, let's examine $(\bar{\boldsymbol{r}}'_{st'}\bar{\boldsymbol{r}}_{st})$. This matrix is equal to (24).

$$\begin{bmatrix} \bar{\boldsymbol{r}}'_{s1}\bar{r}_{st} \\ \bar{\boldsymbol{r}}'_{s2}\bar{r}_{st} \\ \vdots \\ \bar{\boldsymbol{r}}'_{st-1}\bar{r}_{st} \\ \bar{\boldsymbol{r}}'_{st+1}\bar{r}_{st} \\ \vdots \\ \bar{\boldsymbol{r}}'_{sT-1}\bar{r}_{st} \\ \bar{\boldsymbol{r}}'_{sT}\bar{r}_{st} \end{bmatrix} \tag{24}$$

Again, under the stationarity assumptions in (22), we can simplify this matrix to (25).

$$\begin{bmatrix} \sigma_{\bar{r}t-1} \\ \sigma_{\bar{r}t-2} \\ \vdots \\ \sigma_{\bar{r}1} \\ \sigma_{\bar{r}1} \\ \vdots \\ \sigma_{\bar{r}T-t-1} \\ \sigma_{\bar{r}T-t} \end{bmatrix} \tag{25}$$

In order to circumvent the tradeoff between number of independent variables and number of observations, I calculate the variance $\sigma^2_{\bar{r}}$ and covariances $\sigma_{\bar{r}y}$ manually using all observations that can contribute to the calculation. I then plug these values back into the matrices in (23) and (25) and then manually perform the matrix algebra necessary to obtain the coefficient vector $\boldsymbol{\beta}_{\bar{r}t'}$. Note that the matrices in (18) through (25) will look slightly different for schools that do not have data for all years. Specifically (18) will not contain values $\bar{r}_{st'}$ for years t' for which the school does not have data. This will then follow into the subsequent matrices. Again, this is the advantage of manually calculating the variances and covariances, as it allows us to use a flexible set of projection variables tailored to each school depending on data availability and to identify coefficients using the maximum amount of available variation.

Figure 14 shows the autocorrelation values $\sigma_{\bar{r}y}$. For all school levels and subjects the correlation between residual values $\bar{r}_{st}$ and $\bar{r}_{st'}$ that are y years apart gradually fades out in an essentially linear fashion. The autocorrelation between years is highest for middle school and similar for elementary and high school.

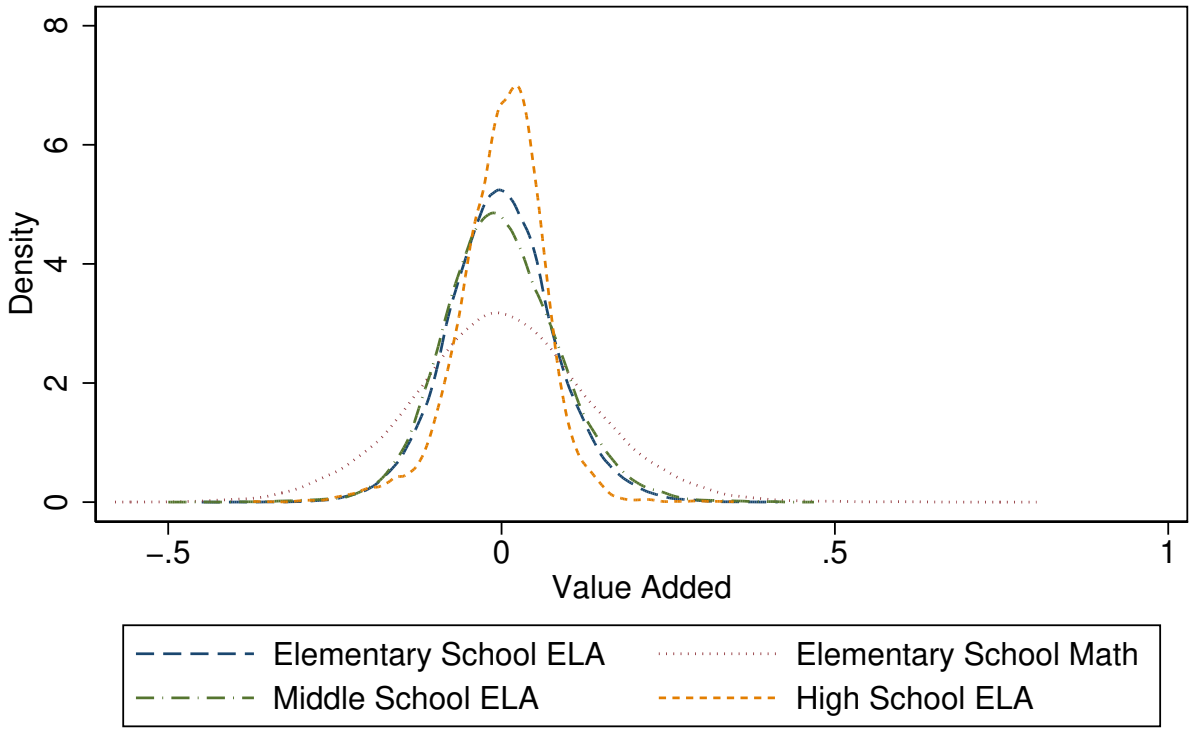
It is important to note that due to the inclusion of a constant in equation (10) the residuals r_{isgt} will sum to zero by definition of the first order conditions of OLS. For this reason, school value added can only be estimated in relative terms. While equation (10) imposes the constraint that $\sum_{i=1}^{N} r_{isgt} = 0$, I rescale the value added estimates such that $\sum_{s=1}^{S} \sum_{t=1}^{T} \hat{\mu}_{st} = 0$, effectively altering the constraint on the value added estimates so that they have mean zero at the school by year level instead of at the student level. This rescaling has no impact on the analyses but simplifies the interpretation of the value added estimates, as a school with positive value added is above average and a school with negative value added is below average.

D Elementary School Math Value Added

E Additional Results

Figure 3 plots the kernel density estimate of the permuted value added estimates from section 3.3.1. These estimates are the value added estimates obtained after randomly assigning students to schools within a grade by year cell. These kernel density estimates illustrate that the actual value added estimates are not merely measuring noise or small sample bias.

List of Figures



Elementary School ELA Mean (Standard Deviation) = 0 (0.081)
Elementary School Math Mean (Standard Deviation) = 0 (0.134)
Middle School ELA Mean (Standard Deviation) = 0 (0.087)
High School ELA Mean (Standard Deviation) = 0 (0.066)

Figure 1: School Test Score Value Added Distributions

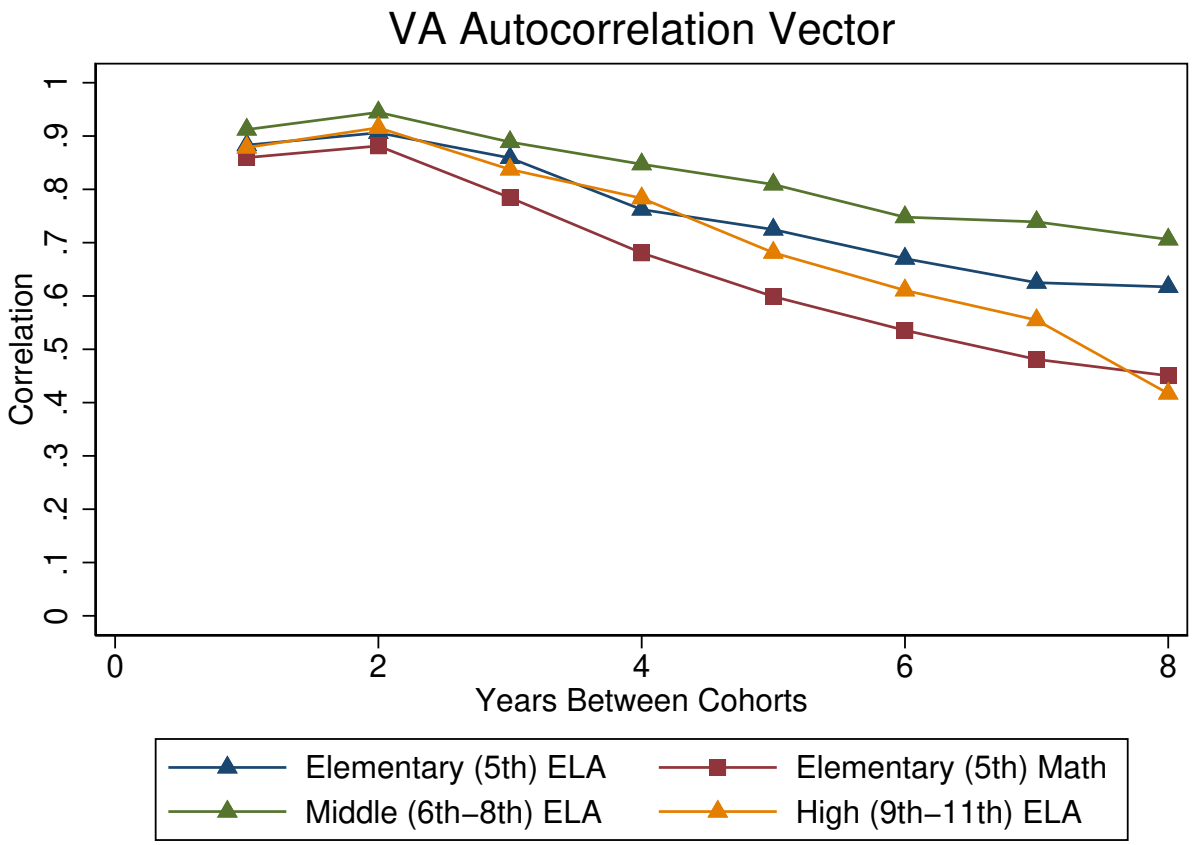
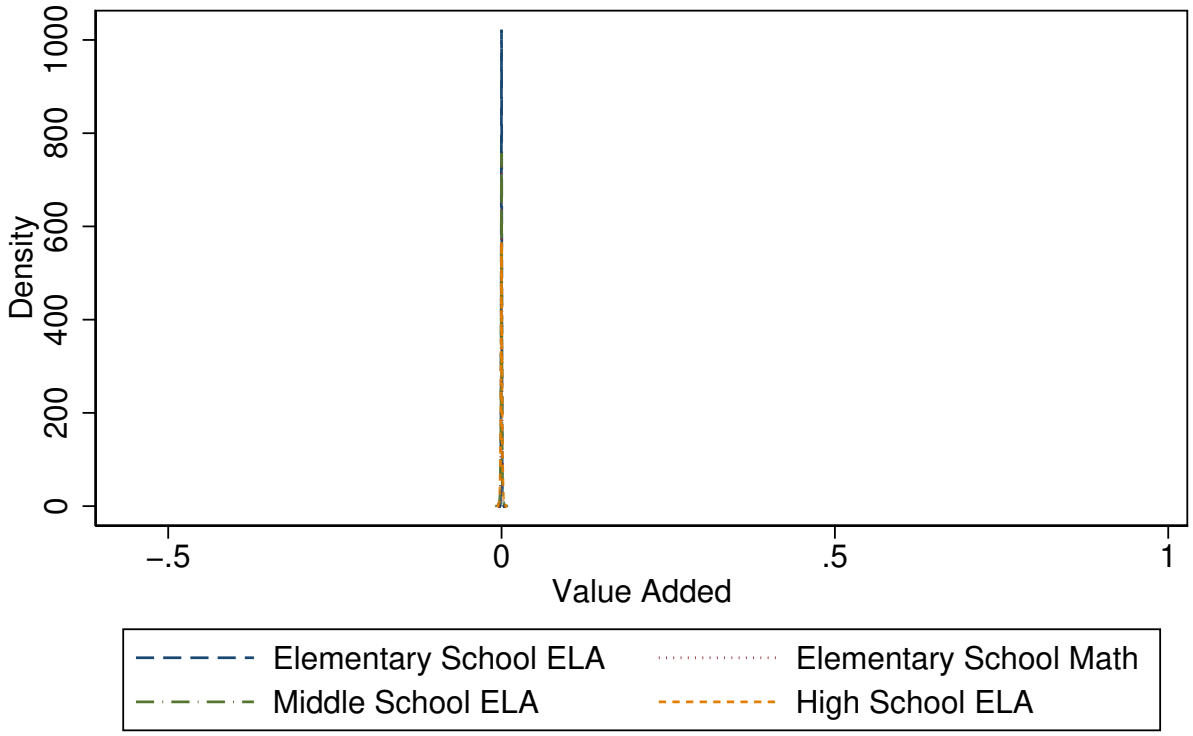
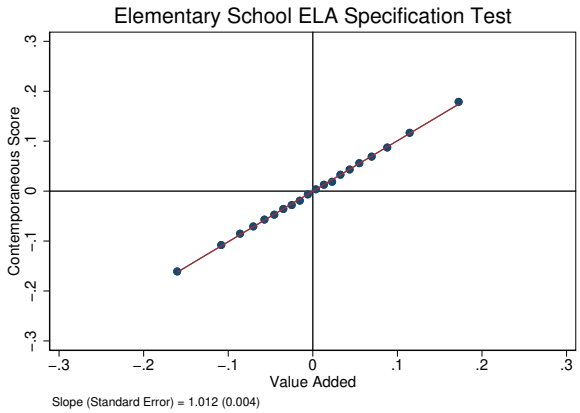


Figure 2: School Test Score Value Added Autocorrelation Vectors

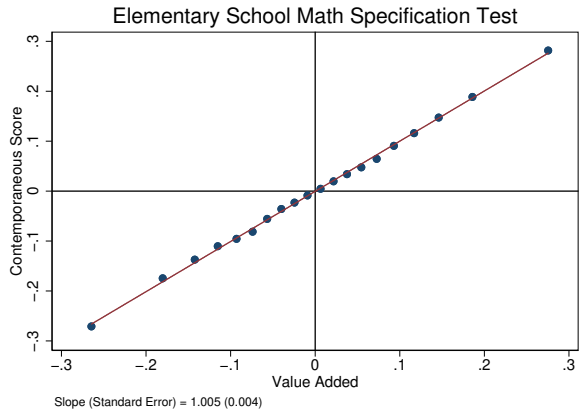


Elementary School ELA Mean (Standard Deviation) = 0 (0.000)
Elementary School Math Mean (Standard Deviation) = 0 (0.001)
Middle School ELA Mean (Standard Deviation) = 0 (0.001)
High School ELA Mean (Standard Deviation) = 0 (0.001)

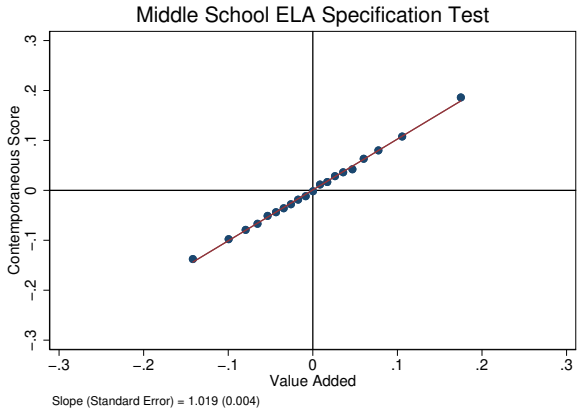
Figure 3: School Test Score Permuted Value Added Distributions



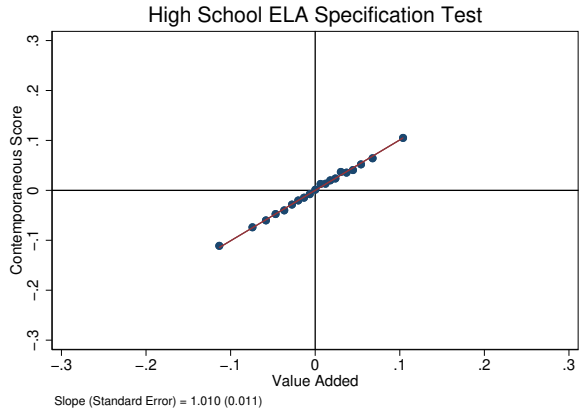
(a) Elementary School ELA



(b) Elementary School Math

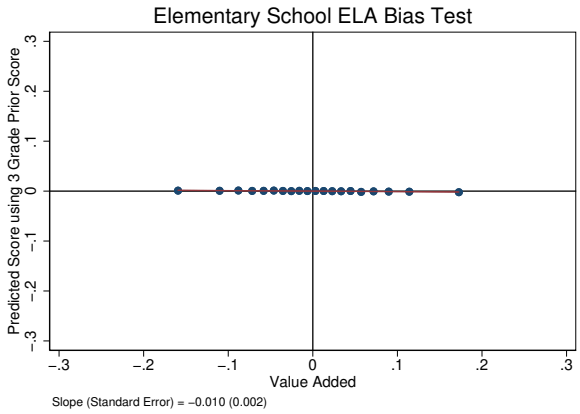


(c) Middle School ELA

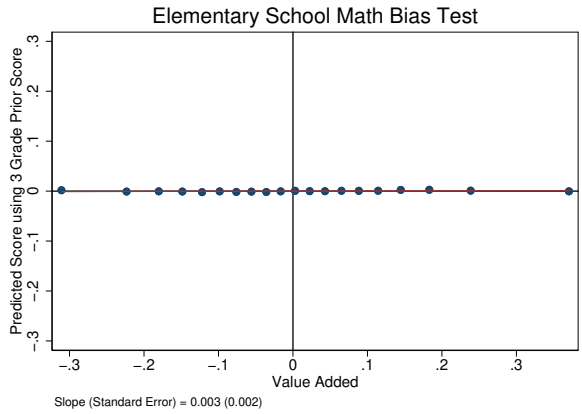


(d) High School ELA

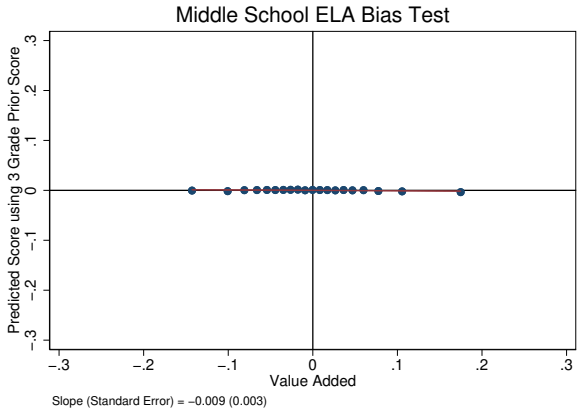
Figure 4: School Test Score Value Added Specification Tests



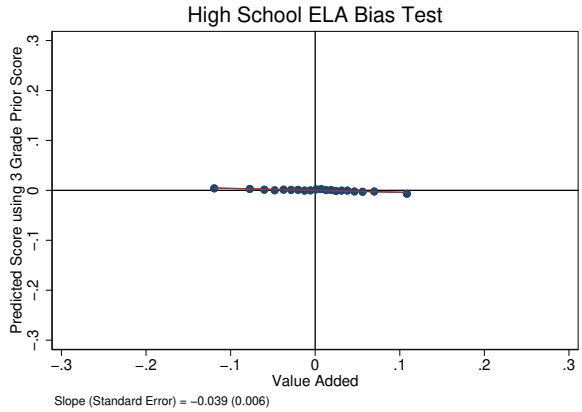
(a) Elementary School ELA



(b) Elementary School Math

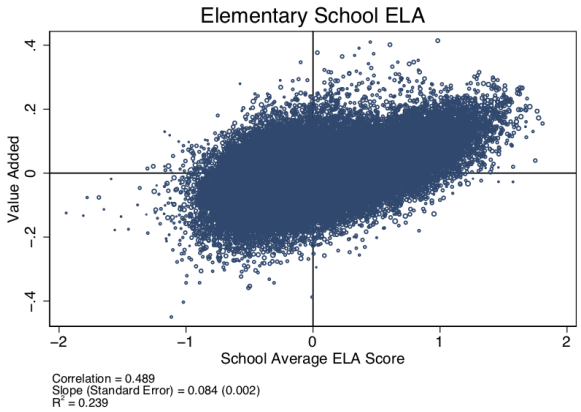


(c) Middle School ELA

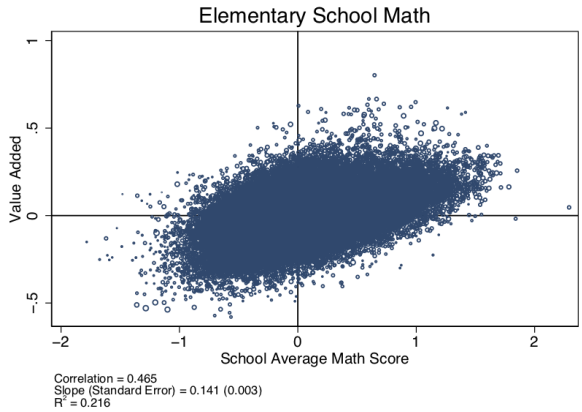


(d) High School ELA

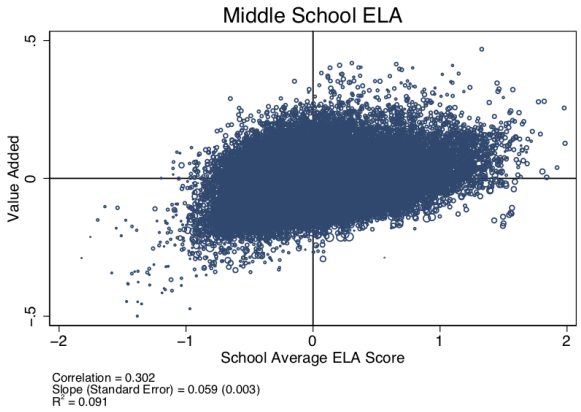
Figure 5: School Test Score Value Added Forecast Bias Tests



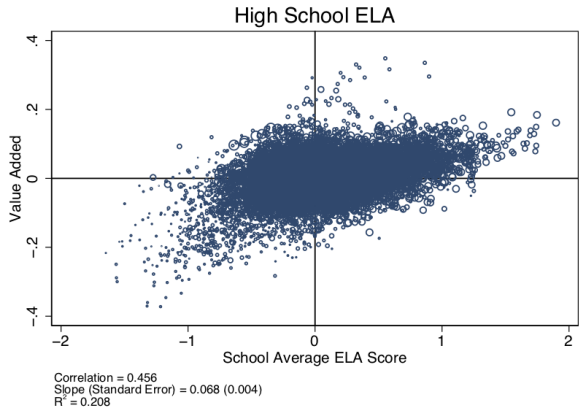
(a) Elementary School ELA



(b) Elementary School Math

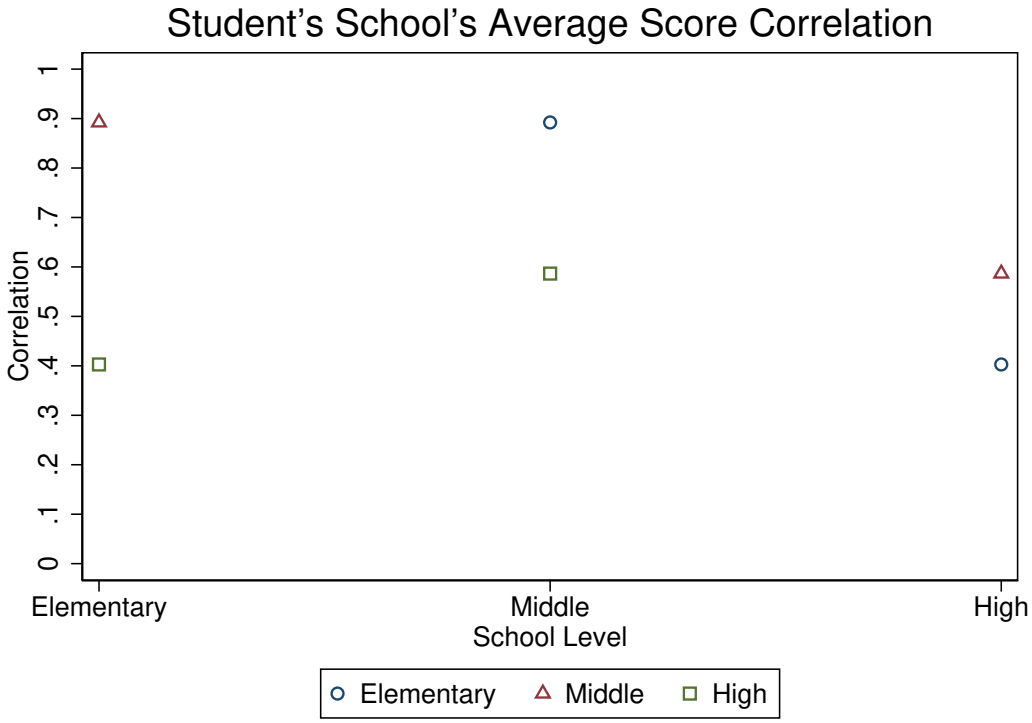


(c) Middle School ELA

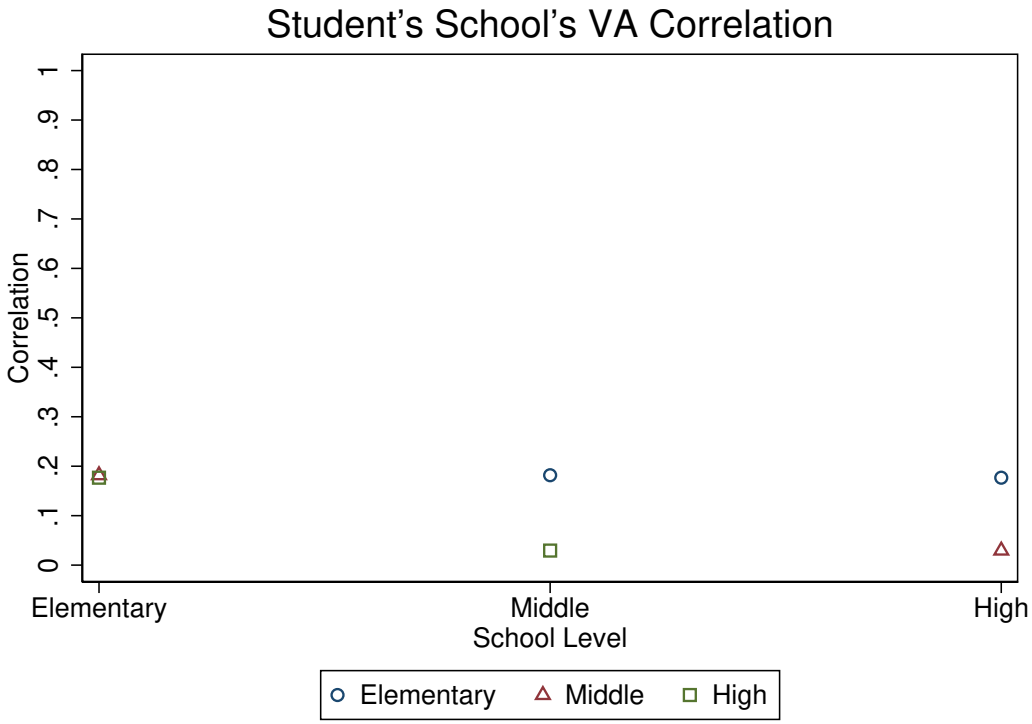


(d) High School ELA

Figure 6: School Test Score Value Added vs. School Average Test Score



(a) School Average Test Score



(b) School Test Score Value Added

Figure 7: Student Correlation Matrix

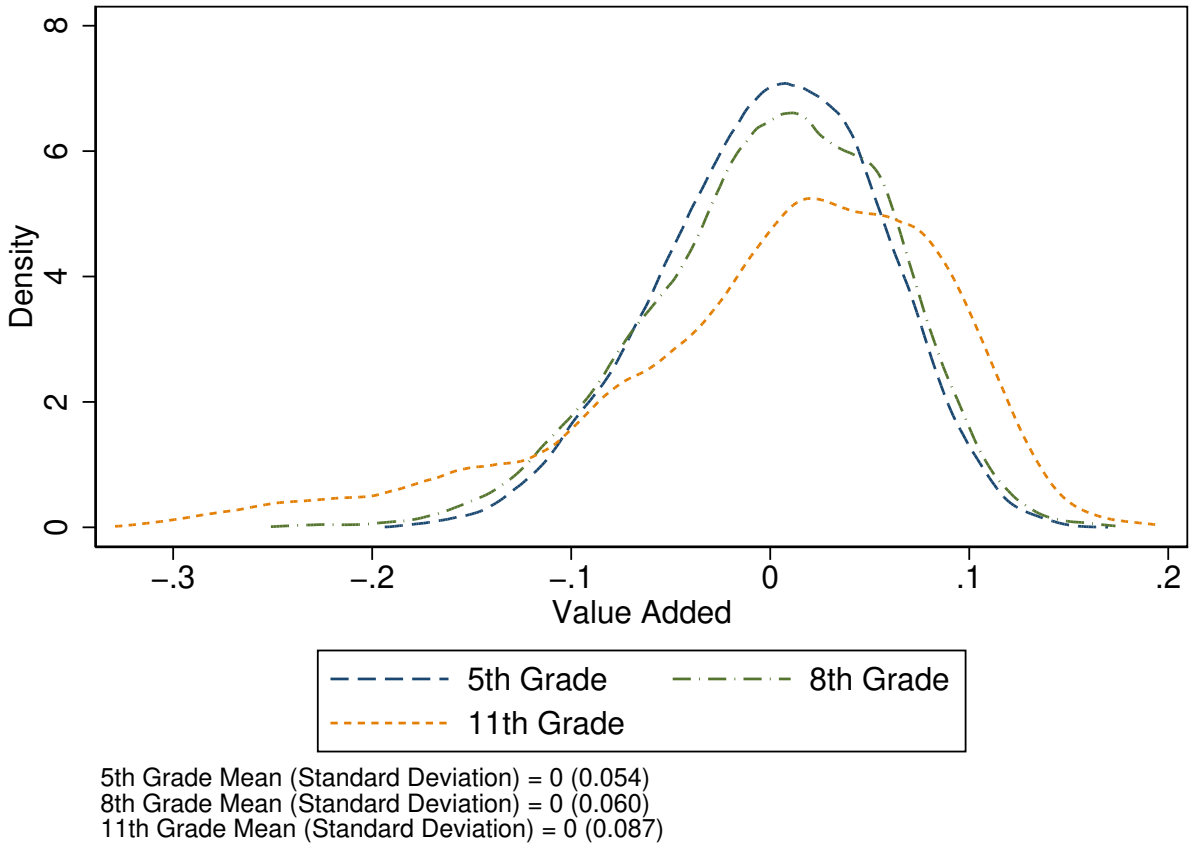
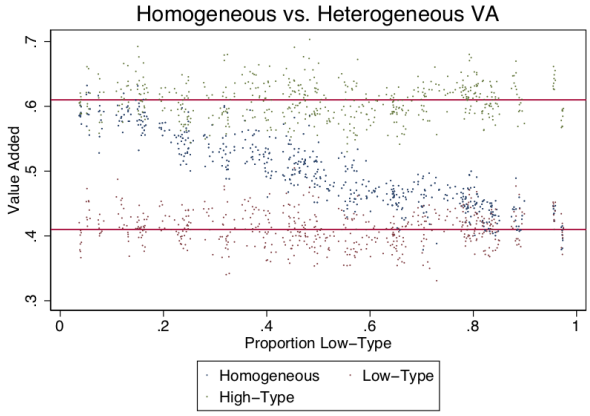
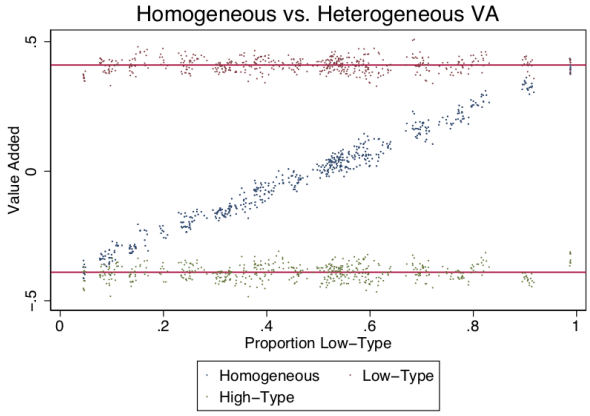


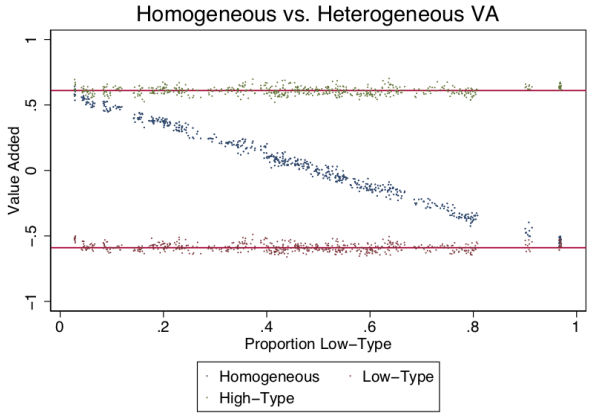
Figure 8: School Postsecondary Enrollment Value Added Distribution



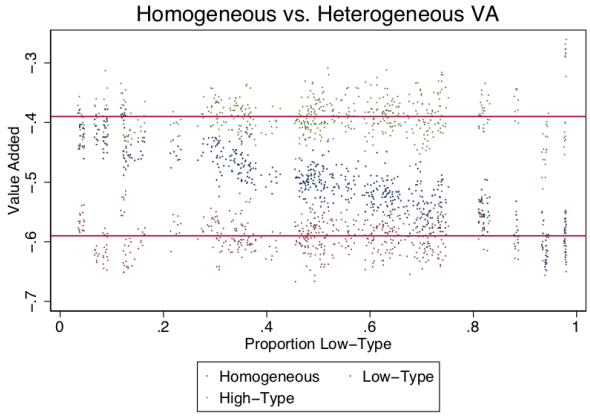
(a) $\mu_{AL} = 0.41$, $\mu_{AH} = 0.61$



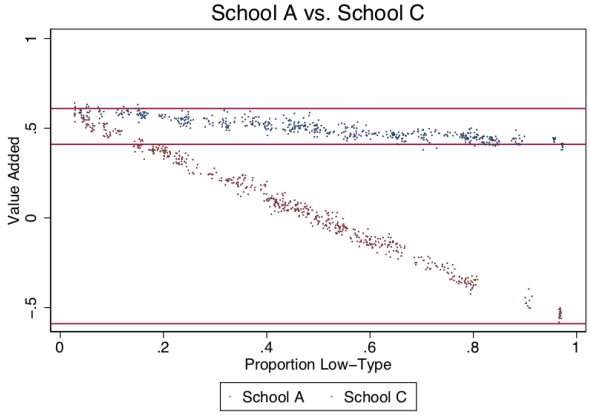
(b) $\mu_{BL} = 0.41$, $\mu_{BH} = -0.39$



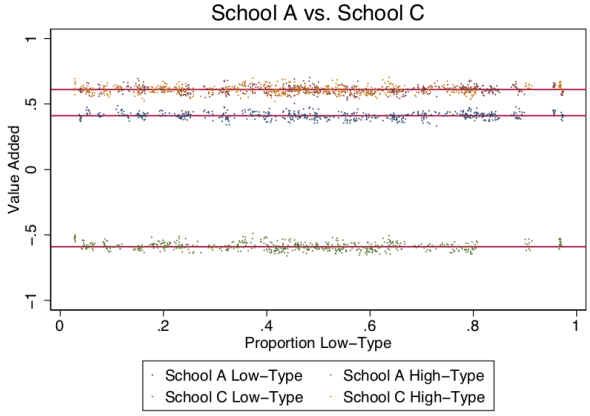
(c) $\mu_{CL} = -0.59$, $\mu_{CH} = 0.61$



(d) $\mu_{DL} = -0.59$, $\mu_{DH} = -0.39$



(e) $\mu_{AL} = 0.41$, $\mu_{CL} = -0.59$, $\mu_{AH} = \mu_{CH} = 0.61$



(f) $\mu_{AL} = 0.41$, $\mu_{CL} = -0.59$, $\mu_{AH} = \mu_{CH} = 0.61$

Figure 9: Value Added Heterogeneity Simulation

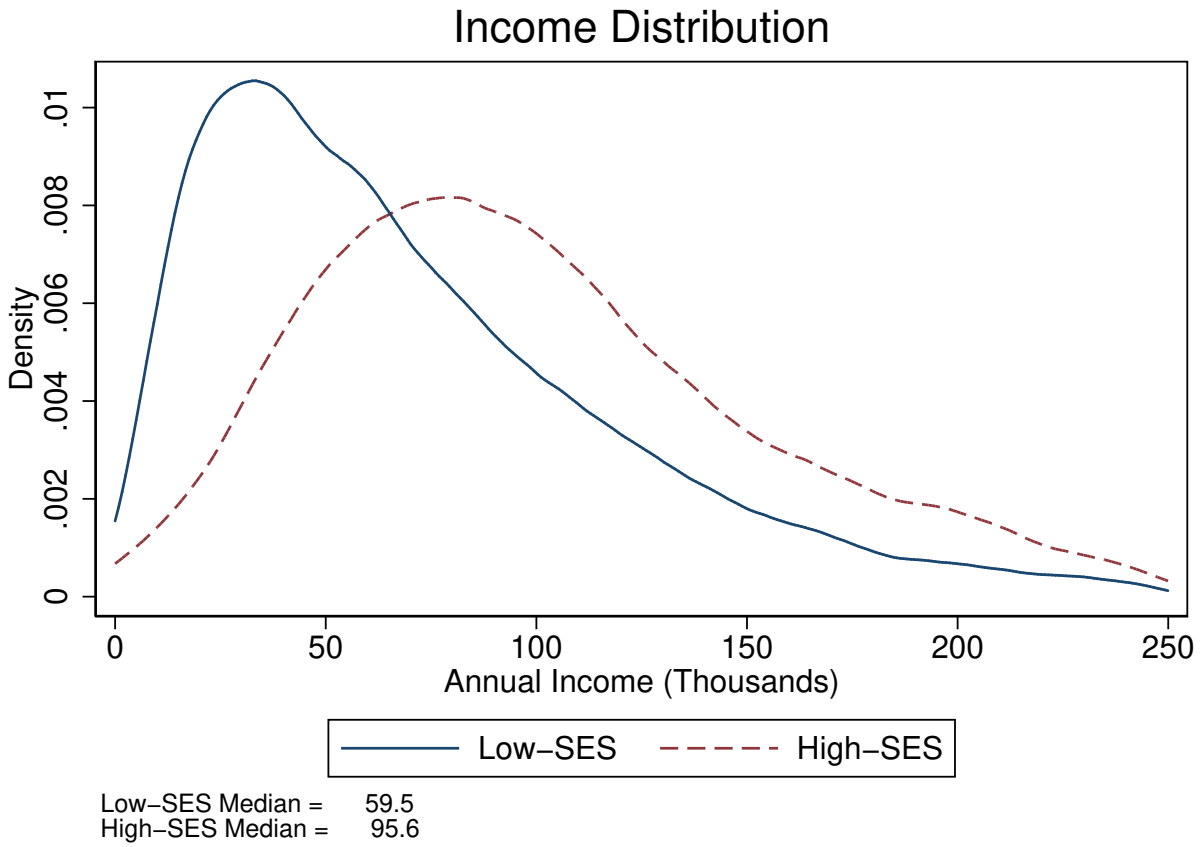
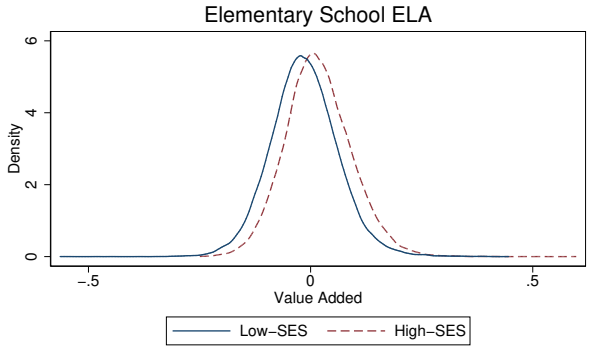
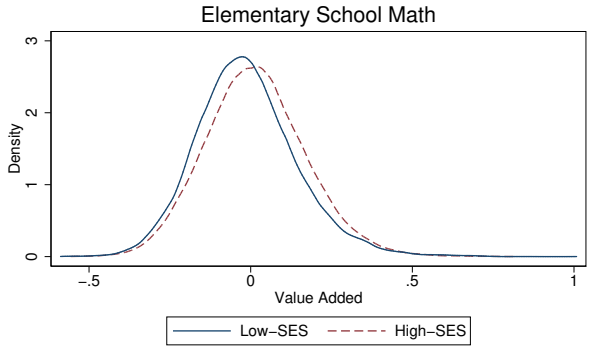


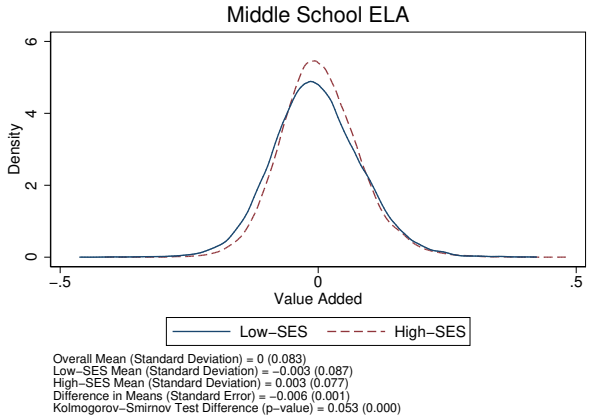
Figure 10: Income Distribution by Economic Disadvantage



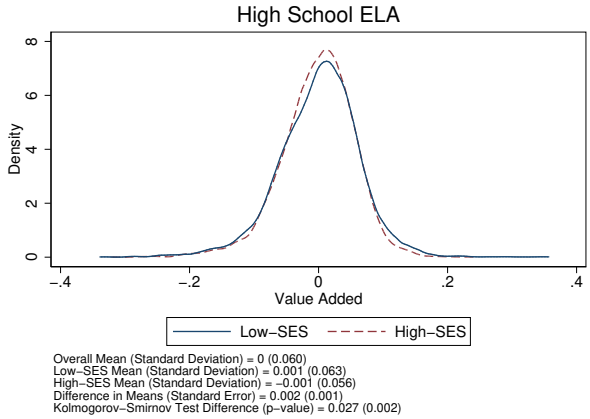
(a) Elementary School ELA



(b) Elementary School Math

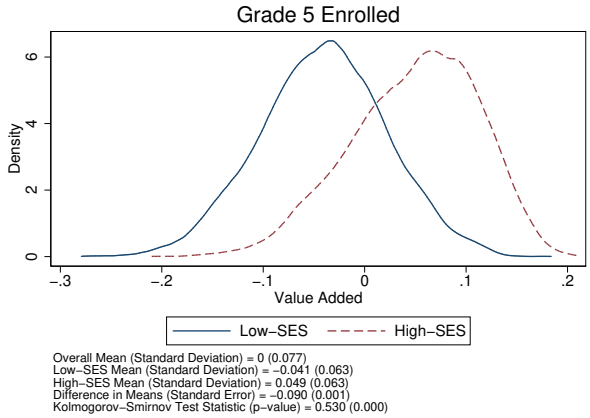


(c) Middle School ELA

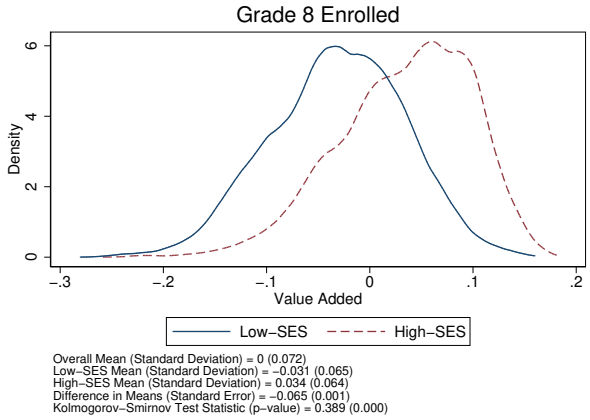


(d) High School ELA

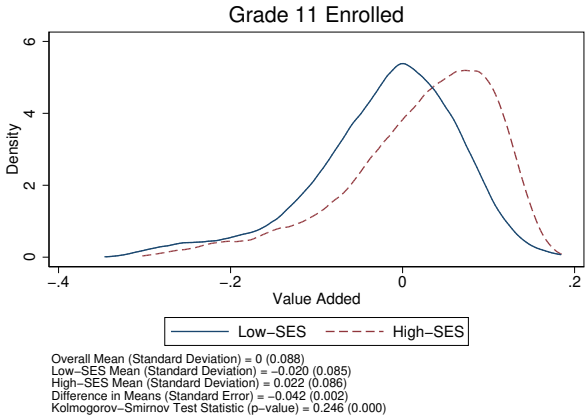
Figure 11: School by Socioeconomic Status Test Score Value Added Distribution



(a) Grade 5

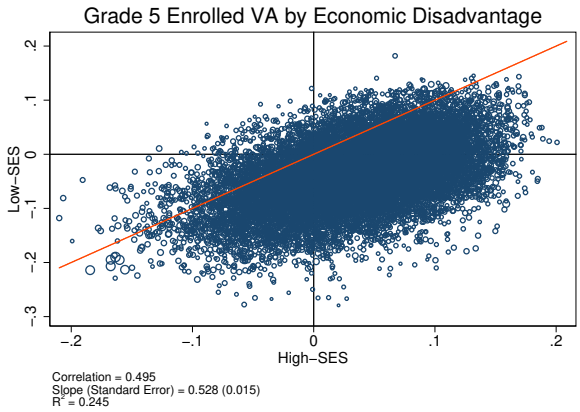


(b) Grade 8

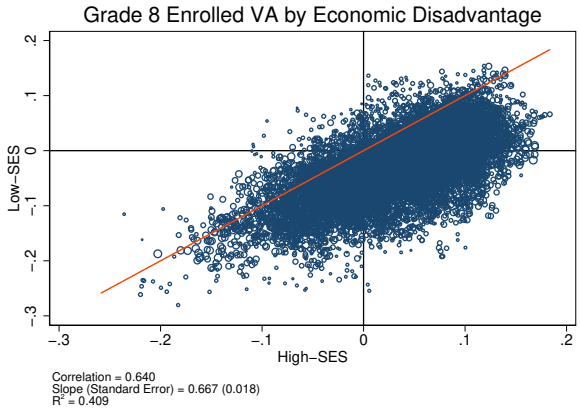


(c) Grade 11

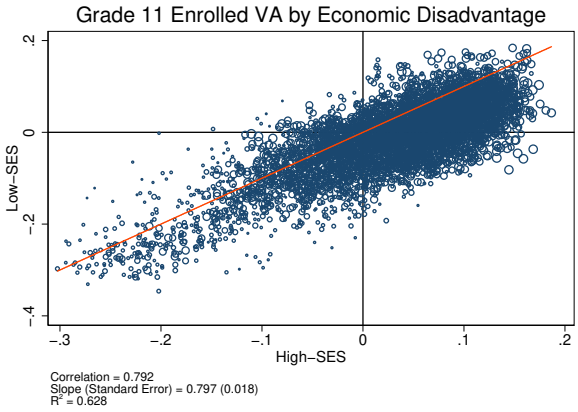
Figure 12: School by Socioeconomic Status Enrolled Value Added Distribution



(a) Elementary School ELA



(b) Middle School ELA



(c) High School ELA

Figure 13: Low-SES vs. High-SES School Value Added

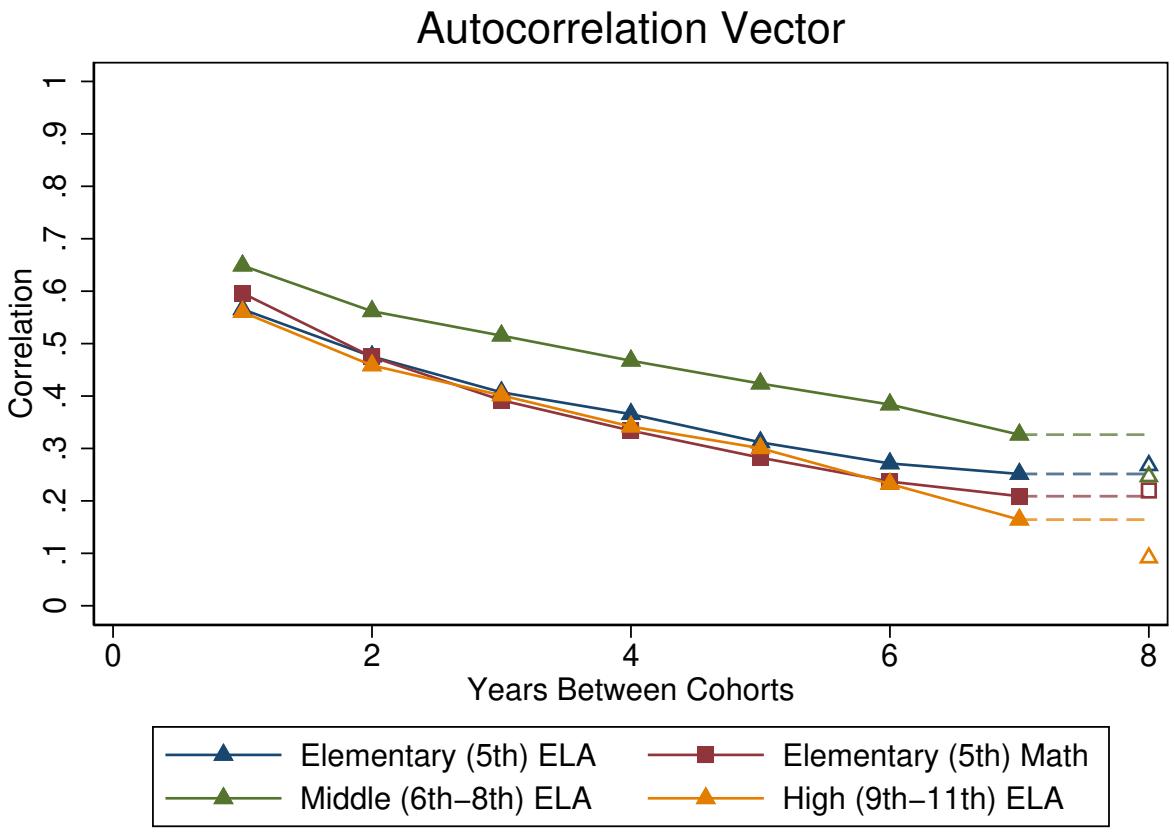


Figure 14: School Autocorrelation Vector

List of Tables

Table 1: K–12 Summary Statistics

	Elementary		Middle	High
	ELA	Math	ELA	ELA
School Controls				
# of Students in School-Grade	104.9	104.9	327.0	526.0
	[47.32]	[47.32]	[202.8]	[279.0]
Demographic Controls				
Age in Years	10.25	10.25	12.77	15.78
	[0.668]	[0.668]	[0.932]	[0.954]
Male	0.513	0.513	0.514	0.513
	[0.500]	[0.500]	[0.500]	[0.500]
Hispanic or Latino	0.520	0.520	0.502	0.476
	[0.500]	[0.500]	[0.500]	[0.499]
White	0.273	0.273	0.285	0.304
	[0.445]	[0.445]	[0.452]	[0.460]
Asian	0.116	0.116	0.118	0.124
	[0.321]	[0.321]	[0.323]	[0.330]
Black or African American	0.0721	0.0721	0.0752	0.0763
	[0.259]	[0.259]	[0.264]	[0.266]
Other Race	0.0262	0.0262	0.0252	0.0262
	[0.160]	[0.160]	[0.157]	[0.160]
Economic Disadvantage	0.603	0.603	0.571	0.498
	[0.489]	[0.489]	[0.495]	[0.500]
Limited English Proficient Status	0.279	0.279	0.194	0.157
	[0.448]	[0.448]	[0.396]	[0.364]
Disabled	0.0777	0.0777	0.0733	0.0655
	[0.268]	[0.268]	[0.261]	[0.247]
Test Scores				
Current Test Score	0.000218	0.000182	0.000380	0.00102
	[1.000]	[1.000]	[1.000]	[1.000]
1 Grade Prior Test Score	0.0427	0.0412	0.0345	0.0796
	[0.986]	[0.988]	[0.989]	[0.984]
2 Grade Prior Test Score	0.0764	0.0742	0.0483	0.0888
	[0.975]	[0.975]	[0.983]	[0.980]
Schools	7,543	7,543	7,294	3,674
Students	4,738,833	4,738,833	5,336,807	5,456,271
Observations	8,641,343	8,641,343	13,069,227	13,316,199

Values are means and standard deviations (in brackets) of the dependent and independent variables used in the value added estimation. Only students included in the test score value added sample are included this table. Data comes from public schools in the state of California between the 2004-2005 and 2012-2013 school years. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11.

Table 2: Datasets

Dataset	Begin	End	Unit of Observation
CST	Spring 2003	Spring 2013	CA public school 2nd-11th graders
NSC	Spring 2010	Spring 2017	Spring 2009-2016 CA public school 11th graders
CSU Application	Fall 2001	Spring 2017	Universe of applicants
CSU Enrollment	Fall 2001	Spring 2017	Universe of enrolled students
CSU Degree	Fall 2001	Spring 2016	Universe of degree recipients
CCC Enrollment	Fall 1992	Spring 2017	Universe of enrolled students
CCC Degree	Fall 1992	Spring 2016	Universe of degree recipients

Table 3: School Test Score Value Added Specification/Forecast Bias Tests

	Elementary		Middle	High
	ELA	Math	ELA	ELA
VA Specification Test: Contemporaneous Score	1.012***	1.005	1.019***	1.010
	(0.004)	(0.004)	(0.004)	(0.011)
	[1.003,1.020]	[0.997,1.013]	[1.011,1.026]	[0.989,1.031]
VA Bias Test: Predicted Score using Prior Score	-0.010***	0.003	-0.009***	-0.039***
	(0.002)	(0.002)	(0.003)	(0.006)
	[-0.015,-0.006]	[-0.001,0.006]	[-0.014,-0.003]	[-0.050,-0.027]

Each cell represents a separate regression. The first row contains the coefficient for a bivariate regression of test score residuals r_{isgt} on school value added $\hat{\mu}_{st}$. Statistical inference is conducted under the null hypothesis that the coefficient equals 1. The second row contains the coefficient for a regression of the projection of test scores onto three grade prior test scores on school value added $\hat{\mu}_{st}$. Statistical inference is conducted under the null hypothesis that the coefficient equals 0. Standard errors cluster bootstrapped at the school level are presented in parentheses. The 95% confidence intervals are presented in brackets.

Table 4: K–12 Outcomes on School Test Score Value Added

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Elementary School ELA	1 Grade Later CST ELA Score	1 Grade Later CST Math Score	Stayed in Public School	Highest Math Subject in Grade 7		Highest Math Subject in Grade 11
Elementary School ELA Value Added	0.088***	0.093***	-0.001***	0.002		0.020***
	(0.001)	(0.002)	(0.000)	(0.001)		(0.002)
Y Mean	0.056	0.050	0.793	0.081		0.373
Observations	4,782,394	4,779,116	5,776,992	3,587,713		640,149
R^2	0.711	0.548	0.784	0.154		0.269
Panel B: Elementary School Math	1 Grade Later CST ELA Score	1 Grade Later CST Math Score	Stayed in Public School	Highest Math Subject in Grade 7		Highest Math Subject in Grade 11
Elementary School Math Value Added	0.059***	0.126***	0.000*	0.004***		0.012***
	(0.002)	(0.001)	(0.000)	(0.001)		(0.002)
Y Mean	0.057	0.052	0.793	0.081		0.374
Observations	4,770,271	4,767,070	5,761,968	3,578,272		639,038
R^2	0.585	0.648	0.784	0.185		0.318
Panel C: Middle School ELA	1 Grade Later CST ELA Score		Stayed in Public School		Highest Math Subject in Grade 9	Highest Math Subject in Grade 11
Middle School ELA Value Added	0.067***		-0.001		-0.001	0.005*
	(0.001)		(0.000)		(0.002)	(0.003)
Y Mean	0.072		0.771		0.062	0.344
Observations	7,010,235		8,528,085		5,758,625	2,900,331
R^2	0.741		0.753		0.137	0.310
Panel D: High School ELA	1 Grade Later CST ELA Score		Stayed in Public School			Highest Math Subject in Grade 11
High School ELA Value Added	0.104***		0.003**			0.009***
	(0.001)		(0.001)			(0.004)
Y Mean	0.084		0.771			0.324
Observations	4,268,621		5,320,860			5,593,418
R^2	0.715		0.697			0.337

Each cell is a separate regression of the outcome listed in the column header on school value added. Panels A-D are differentiated by which school level value added is included as an independent variable. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11. Each regression also includes the controls included in the estimation of school value added. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 5: Postsecondary Summary Statistics

	Elementary	Middle	High
Enrolled at a Postsecondary Institution	0.629	0.630	0.620
	[0.483]	[0.483]	[0.485]
Enrolled at a 2-Year College	0.367	0.373	0.372
	[0.482]	[0.484]	[0.483]
Enrolled at a 4-Year University	0.262	0.258	0.248
	[0.440]	[0.437]	[0.432]
Enrolled at a Public Institution	0.574	0.573	0.560
	[0.495]	[0.495]	[0.496]
Enrolled at a Private Institution	0.055	0.057	0.060
	[0.229]	[0.232]	[0.237]
Enrolled at a CA Institution	0.569	0.571	0.561
	[0.495]	[0.495]	[0.496]
Enrolled at an Out-of-State Institution	0.060	0.059	0.058
	[0.238]	[0.236]	[0.234]
Observations	4,291,249	4,355,400	4,201,902

Values are means and standard deviations (in brackets) of the dependent and independent variables used in the value added estimation. Only students included in the test score value added sample are included this table. Data comes from public schools in the state of California between the 2004-2005 and 2012-2013 school years. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11.

Table 6: Postsecondary Enrollment on School Test Score Value Added

Panel A: Elementary School ELA	(1) Enrolled	(2) Enrolled 2-Year	(3) Enrolled 4-Year
Elementary School ELA Value Added	0.016***	-0.009***	0.024***
	(0.001)	(0.001)	(0.001)
Y Mean	0.652	0.369	0.283
Observations	2,634,986	2,634,986	2,634,986
R^2	0.113	0.027	0.191
Panel B: Elementary School Math	Enrolled	Enrolled 2-Year	Enrolled 4-Year
Elementary School Math Value Added	0.005***	-0.011***	0.016***
	(0.001)	(0.001)	(0.001)
Y Mean	0.652	0.369	0.283
Observations	2,627,847	2,627,847	2,627,847
R^2	0.116	0.026	0.194
Panel C: Middle School ELA	Enrolled	Enrolled 2-Year	Enrolled 4-Year
Middle School ELA Value Added	0.018***	0.007***	0.011***
	(0.001)	(0.002)	(0.002)
Y Mean	0.649	0.374	0.276
Observations	6,255,894	6,255,894	6,255,894
R^2	0.119	0.033	0.207
Panel D: High School ELA	Enrolled	Enrolled 2-Year	Enrolled 4-Year
High School ELA Value Added	0.022***	-0.006**	0.028***
	(0.002)	(0.003)	(0.003)
Y Mean	0.656	0.382	0.273
Observations	6,077,068	6,077,068	6,077,068
R^2	0.125	0.042	0.224

Each cell is a separate regression of the outcome listed in the column header on school value added. Panels A-D are differentiated by which school level value added is included as an independent variable. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11. Each regression also includes the controls included in the estimation of school value added. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 7: Postsecondary Enrollment on Horse Race of School Test Score Value Added

	(1) Enrolled	(2) Enrolled 2-Year	(3) Enrolled 4-Year
Elementary	0.002***	-0.008***	0.010***
	(0.001)	(0.001)	(0.001)
Middle	0.005***	0.020***	-0.015***
	(0.001)	(0.001)	(0.001)
High	0.022***	-0.004***	0.025***
	(0.001)	(0.001)	(0.001)
Elementary × Middle	0.002***	-0.003***	0.005***
	(0.001)	(0.001)	(0.001)
Middle × High	-0.004***	0.001	-0.005***
	(0.001)	(0.001)	(0.001)
Elementary × High	-0.003***	-0.004***	0.001*
	(0.001)	(0.001)	(0.001)
Elementary × Middle × High	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Y Mean	0.680	0.382	0.299
Observations	1,068,507	1,068,507	1,068,507
R^2	0.132	0.051	0.246

Each column is a separate regression of the outcome listed in the column header on school value added. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11. Each regression also includes the controls included in the estimation of school value added, averaged across grades. Heteroskedasticity-robust standard errors are presented in parentheses.

Table 8: CSU Outcomes on School Value Added

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Elementary School ELA	Accepted	Eng. Rem.	Math Rem.	STEM Major	Undecided	Persist to Year 2	Persist to Year 3		
Elementary School ELA Value Added	-0.006***	-0.021***	-0.024***	0.001	-0.019***	0.012***	0.014***		
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
Y Mean	0.779	0.231	0.246	0.342	0.210	0.835	0.759		
Observations	708,403	289,034	289,034	290,356	290,356	224,867	171,846		
R^2	0.067	0.198	0.161	0.019	0.030	0.033	0.032		
Panel B: Elementary School Math	Accepted	Eng. Rem.	Math Rem.	STEM Major	Undecided	Persist to Year 2	Persist to Year 3		
Elementary School Math Value Added	-0.006***	-0.003**	-0.004**	0.000	-0.011***	0.002	0.004**		
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
Y Mean	0.779	0.231	0.246	0.342	0.210	0.835	0.759		
Observations	707,312	288,615	288,615	289,938	289,938	224,560	171,627		
R^2	0.070	0.157	0.196	0.024	0.029	0.033	0.033		
Panel C: Middle School ELA	Accepted	Eng. Rem.	Math Rem.	STEM Major	Undecided	Persist to Year 2	Persist to Year 3	Degree	STEM Degree
Middle School ELA Value Added	-0.005***	-0.022***	-0.032***	-0.000	-0.018***	0.012***	0.014***	0.002	-0.003
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Y Mean	0.806	0.231	0.228	0.332	0.197	0.853	0.771	0.838	0.452
Observations	1,880,746	833,026	833,023	836,271	836,271	699,197	564,757	168,301	89,761
R^2	0.069	0.166	0.126	0.017	0.017	0.027	0.029	0.238	0.505
Panel D: High School ELA	Accepted	Eng. Rem.	Math Rem.	STEM Major	Undecided	Persist to Year 2	Persist to Year 3	Degree	STEM Degree
High School ELA Value Added	-0.006***	-0.000	-0.008**	-0.001	-0.005	0.002	0.002	0.003	0.002
	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.002)	(0.003)	(0.003)	(0.002)
Y Mean	0.841	0.233	0.215	0.317	0.187	0.860	0.775	0.715	0.270
Observations	2,410,027	1,207,064	1,207,065	1,212,166	1,212,166	1,114,516	940,304	596,624	469,116
R^2	0.059	0.122	0.089	0.018	0.015	0.020	0.024	0.101	0.190

Each cell is a separate regression of the outcome listed in the column header on school value added. Panels A-D are differentiated by which school level value added is included as an independent variable. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11. Each regression also includes the controls included in the estimation of school value added. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 9: CCC Outcomes on School Value Added

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Elementary School ELA	Eng. Rem.	Math Rem.	Persist to Year 2	Transfered to 4-Year University	Degree	Associate's
Elementary School ELA Value Added	-0.005***	-0.005***	0.007***	0.026***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Y Mean	0.209	0.202	0.709	0.303	0.441	0.408
Observations	1,389,266	1,389,266	961,492	1,143,640	228,702	220,215
R^2	0.151	0.105	0.077	0.161	0.211	0.196
Panel B: Elementary School Math	Eng. Rem.	Math Rem.	Persist to Year 2	Transfered to 4-Year University	Degree	Associate's
Elementary School Math Value Added	-0.005***	-0.005***	0.001	0.015***	0.008***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Y Mean	0.209	0.202	0.710	0.303	0.441	0.408
Observations	1,386,019	1,386,019	959,316	1,140,898	228,319	219,857
R^2	0.138	0.120	0.079	0.165	0.215	0.201
Panel C: Middle School ELA	Eng. Rem.	Math Rem.	Persist to Year 2	Transfered to 4-Year University	Degree	Associate's
Middle School ELA Value Added	0.004	0.000	0.012***	0.010***	0.013***	0.013***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Y Mean	0.243	0.233	0.718	0.343	0.385	0.363
Observations	3,449,346	3,449,346	2,819,184	3,022,127	1,538,989	1,521,853
R^2	0.161	0.106	0.062	0.181	0.155	0.161
Panel D: High School ELA	Eng. Rem.	Math Rem.	Persist to Year 2	Transfered to 4-Year University	Degree	Associate's
High School ELA Value Added	-0.003	-0.004	0.013***	0.030***	0.015***	0.015***
	(0.004)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Y Mean	0.269	0.259	0.705	0.362	0.315	0.289
Observations	4,517,170	4,517,170	4,225,586	3,458,369	3,448,378	3,434,926
R^2	0.163	0.105	0.056	0.199	0.158	0.175

Each cell is a separate regression of the outcome listed in the column header on school value added. Panels A-D are differentiated by which school level value added is included as an independent variable. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11. Each regression also includes the controls included in the estimation of school value added. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 10: Rank Example Value Added

s	μ_{sLt}	μ_{sHt}	$p(s = S)$
A	0.41	0.61	0.25
B	0.41	-0.39	0.25
C	-0.59	0.61	0.25
D	-0.59	-0.39	0.25

Table 11: Rank Example Parameters

$\theta_{st} \sim \mathcal{N}(0, 0.05)$
$\varepsilon_{isdt} \sim \mathcal{N}(0, 0.5)$
$N_{sLt}, N_{sHt} \sim U[7, 1007]$
$j_{sdt} \sim U[1, 1.1]$
# of Schools = 250
# of Years = 9

Table 12: School Value Added Characteristics

	Test Score				Enrollment			
	Elementary		Middle	High	Elementary		Middle	High
	ELA	Math	ELA	ELA	ELA	Math	ELA	ELA
FTE Teachers per Student	5.86***	5.25***	-3.62*	-.455	-16.9***	-15.9***	-12.2***	4.94*
	(2.04)	(1.96)	(2.13)	(3.05)	(2.02)	(2.02)	(2.44)	(2.62)
FTE Pupil Services per Student	3.4	2.62	-32.4***	-5.09	-10	-4.75	-19.1	16.1**
	(5.32)	(5.41)	(7.53)	(9.41)	(7.13)	(6.87)	(11.8)	(8)
English Learner Staff Per Student	-.524	-.499	3.73**	3.87**	2.39	1.74	3.1	-1.49
	(.98)	(1.1)	(1.85)	(1.8)	(1.62)	(1.43)	(3.1)	(1.61)
Proportion $\leq$ 3 Years Experience Teachers	.158*	.281***	-.241**	.0353	-.273***	-.212**	-.146	.227
	(.086)	(.0916)	(.0967)	(.215)	(.0896)	(.0938)	(.101)	(.175)
Proportion Full Credential Teachers	.404**	.464***	1.17***	-.413*	-.443***	-.425**	.085	.26
	(.167)	(.168)	(.159)	(.219)	(.159)	(.166)	(.181)	(.195)
Proportion Male Teachers	2.04	2.54	1.69	3.51	2.01	2.43	-.216	3.49
	(2.04)	(1.98)	(1.55)	(2.9)	(1.94)	(1.88)	(1.39)	(2.42)
Enrollment Proportion Male	.865	1.64**	1.87**	.103	.326	.501	-.355	1.07
	(.698)	(.714)	(.835)	(2.66)	(.7)	(.65)	(.749)	(2.11)
Proportion Male Teachers×Enrollment Proportion Male	-5.58	-5.73	-8.51***	-6.48	-5.09	-6.08*	-1.16	-4.71
	(3.94)	(3.83)	(3.02)	(5.76)	(3.77)	(3.66)	(2.7)	(4.68)
Staff Proportion Minority	-.559*	-1.22***	-.208	-1.41***	.825***	.74***	.587*	.386
	(.288)	(.28)	(.301)	(.522)	(.275)	(.274)	(.327)	(.524)
Enrollment Proportion Minority	-.598***	-.494***	.0616	-.328*	-1.83***	-1.9***	-1.46***	-1***
	(.0784)	(.0811)	(.086)	(.189)	(.0832)	(.081)	(.114)	(.145)
Staff Proportion Minority×Enrollment Proportion Minority	1.22***	1.86***	.935***	2.02***	.225	.124	.611	.609
	(.317)	(.315)	(.349)	(.698)	(.311)	(.307)	(.391)	(.609)
Total Enrollment (Thousands)	-.00567	.273***	-.294***	.19***	-.13**	-.171***	.0201	.205***
	(.0513)	(.0567)	(.034)	(.0305)	(.0523)	(.0529)	(.0389)	(.0276)
Constant	-.754*	-1.43***	-1.21***	.0679	2.1***	2.06***	1.48***	-1.55
	(.423)	(.418)	(.467)	(1.36)	(.42)	(.4)	(.451)	(1.1)
Observations	20,519	20,520	15,734	4,573	20,163	20,164	15,458	3,200
R^2	.0216	.0172	.279	.073	.169	.205	.122	.145

Each column represents a separate regression of value added on school characteristics. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 13: School Value Added Characteristics

	Test Scores				Enrollment			
	Elementary		Middle	High	Elementary		Middle	High
	ELA	Math	ELA	ELA	ELA	Math	ELA	ELA
Instruction Expenditures ($1,000s) per Student	.00171	.00608	.00955	-.00234	.0151***	.00968*	.017***	.00282
	(.0074)	(.00436)	(.00622)	(.00688)	(.00547)	(.00506)	(.0065)	(.00641)
Pupil Services Expenditures ($1,000s) per Student	-.12***	-.114***	-.153***	-.05	-.391***	-.421***	-.311***	-.162***
	(.0334)	(.0278)	(.0246)	(.0362)	(.0443)	(.0483)	(.0301)	(.0345)
Ancillary Services Expenditures ($1,000s) per Student	.257**	.059	-.0197	.0143	.69***	.758***	.0831	.0865
	(.104)	(.115)	(.0824)	(.0691)	(.245)	(.229)	(.111)	(.0823)
Other Expenditures ($1,000s) per Student	.02***	.0223***	-.00499	.00973	.0114***	.0105***	.0149***	.0124*
	(.00323)	(.0033)	(.0035)	(.00654)	(.00336)	(.00344)	(.00412)	(.00732)
General Administration Expenditures ($1,000s) per Student	-.00408	-.00544	.031***	.00239	.0547***	.066***	.0507***	.0182
	(.0166)	(.00908)	(.0111)	(.0145)	(.0167)	(.0135)	(.0166)	(.012)
Total Enrollment (Thousands)	-.083*	.235***	-.509***	.21***	-.186***	-.281***	-.0272	.291***
	(.0462)	(.0553)	(.0324)	(.0238)	(.0539)	(.0553)	(.0432)	(.0227)
Constant	.0416	-.15***	.418***	-.252***	.326***	.445***	.168***	-.263***
	(.0486)	(.047)	(.0432)	(.0634)	(.0563)	(.0603)	(.0499)	(.0621)
Observations	34,790	34,790	26,901	9,708	21,109	21,108	23,237	8,317
R^2	.00924	.0134	.0482	.0582	.0338	.0412	.0343	.132

Each column represents a separate regression of value added on school characteristics. Standard errors cluster bootstrapped at the school level are presented in parentheses.

Table 14: K–12 Counts

	Elementary		Middle	High
	ELA	Math	ELA	ELA
All Students	8,533,348	8,533,348	12,976,007	13,232,134
+ Nonmissing Test Score	8,104,810	8,104,810	12,395,493	12,770,573
+ First Test Score for Grade	7,857,137	7,857,137	11,930,098	12,089,459
+ Conventional School	7,720,543	7,720,543	11,657,560	11,164,330
+ School Size > 10	7,719,862	7,719,862	11,656,772	11,163,636
+ Nonmissing Subject Test Score	7,688,015	7,681,991	11,599,425	11,021,578
+ Nonmissing Demographic Controls	7,380,519	7,375,086	11,184,642	10,664,530
+ Nonmissing 1 Grade Prior Test Score	6,574,347	6,563,929	9,848,334	9,202,521
+ Nonmissing 2 Grade Prior Test Score	5,794,367	5,779,309	8,549,077	7,913,160
+ Nonmissing Peer Controls	5,793,109	5,778,066	8,547,750	7,912,702
+ School VA Sample Size ≥ 7	5,785,167	5,770,100	8,541,805	7,911,067

Values are counts of the number of observations in each sample. Each row is additive, so the restrictions from all prior rows are also present in the current row. Data comes from public schools in the state of California between the 2004-2005 and 2012-2013 school years. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11.

Table 15: K–12 Summary Statistics

	Elementary				Middle		High	
	ELA		Math		ELA		ELA	
	Included	Excluded	Included	Excluded	Included	Excluded	Included	Excluded
School Controls								
# of Students in School-Grade	104	107	104	107	326	328	549	492
	[43.6]	[54.1]	[43.6]	[54]	[193]	[220]	[234]	[332]
Demographic Controls								
Age in Years	10.2	10.3	10.2	10.3	12.7	12.8	15.7	15.9
	[.644]	[.71]	[.644]	[.71]	[.921]	[.948]	[.922]	[.991]
Male	.498	.544	.498	.544	.497	.544	.495	.538
	[.5]	[.498]	[.5]	[.498]	[.5]	[.498]	[.5]	[.499]
Hispanic or Latino	.524	.51	.524	.51	.51	.488	.472	.481
	[.499]	[.5]	[.499]	[.5]	[.5]	[.5]	[.499]	[.5]
White	.273	.272	.273	.272	.284	.289	.31	.296
	[.445]	[.445]	[.445]	[.445]	[.451]	[.453]	[.463]	[.456]
Asian	.122	.105	.122	.105	.125	.106	.137	.104
	[.327]	[.307]	[.327]	[.306]	[.33]	[.308]	[.344]	[.306]
Black or African American	.0617	.0938	.0615	.094	.0632	.0983	.0617	.0981
	[.241]	[.292]	[.24]	[.292]	[.243]	[.298]	[.241]	[.297]
Other Race	.0197	.0395	.0196	.0394	.0188	.0372	.0189	.037
	[.139]	[.195]	[.139]	[.195]	[.136]	[.189]	[.136]	[.189]
Economic Disadvantage	.595	.619	.595	.62	.567	.579	.492	.508
	[.491]	[.486]	[.491]	[.485]	[.495]	[.494]	[.5]	[.5]
Limited English Proficient Status	.251	.337	.251	.336	.161	.259	.12	.212
	[.433]	[.473]	[.433]	[.472]	[.367]	[.438]	[.325]	[.409]
Disabled	.041	.163	.0409	.162	.0387	.147	.0434	.101
	[.198]	[.369]	[.198]	[.369]	[.193]	[.354]	[.204]	[.301]
Test Scores								
Current Test Score	.0568	-.144	.0541	-.136	.0688	-.155	.135	-.23
	[.982]	[1.03]	[.991]	[1.01]	[.979]	[1.03]	[.965]	[1.02]
1 Grade Prior Test Score	.0801	-.145	.0779	-.141	.0769	-.161	.156	-.182
	[.973]	[1.03]	[.978]	[1.02]	[.974]	[1.03]	[.961]	[1.02]
2 Grade Prior Test Score	.102	-.172	.1	-.171	.0794	-.348	.157	-.374
	[.968]	[1.02]	[.966]	[1.02]	[.975]	[1]	[.964]	[.962]
Schools	6,036	7,543	6,035	7,543	5,068	7,292	1,593	3,674
Students	3,407,230	1,844,000	3,400,121	1,853,176	3,903,559	2,448,072	3,819,155	2,901,514
Observations	5,785,167	2,856,176	5,770,100	2,871,243	8,541,805	4,527,422	7,911,067	5,405,132

Values are means and standard deviations (in brackets) of the dependent and independent variables used in the value added estimation. The included column contains students included in the value added estimation, while the excluded column contains students who were excluded from the value added estimation. Data comes from public schools in the state of California between the 2004-2005 and 2012-2013 school years. Elementary school includes grades 4-5, middle school includes grades 6-8, and high school includes grades 9-11.