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Teacher Effectiveness in Urban High Schools

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ABSTRACT

This research examines whether teacher licensure test scores and other teacher qualifications affect high school student achievement. The results are based on longitudinal student-level data from Los Angeles. The achievement analysis uses a value-added approach that adjusts for both student and teacher fixed effects. The results show little relationship between traditional measures of teacher quality (e.g., experience and education level) and student achievement in English Language Arts (ELA) or math. Similarly, teacher aptitude and subject-matter knowledge, as measured on state licensure tests, have no significant effects on student achievement. Achievement outcomes differ substantially from teacher to teacher, however, and the effects of a good ELA or math teacher spillover from one subject to the other.

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1. Introduction

A major concern for educators and policymakers is the low high school graduation rates and weak preparation of high school graduates for postsecondary education and careers. Greene and Forester (2003) show that only 70 percent of public high school students graduate on time and only 32 percent of these graduates have sufficient high school course preparation to attend four-year colleges. The situation is even worse for minority students, with only 50 percent of Black and Hispanic students graduating from high school on time and only about 18 percent of these students qualifying to attend four-year colleges.

Many high school completers are not proficient in basic academic skills needed for postsecondary education and careers. The percentage of twelfth-grade students at or above proficiency levels is only 36 in reading, 26 in writing, 16 in mathematics, and 18 in science (National, 2007). About 42 and 30 percent of freshman at four- and two-year colleges, respectively, take remedial classes (Martorell and McFarlin, 2007). Moreover, students fall behind in college as they complete remedial classes, and this delay and the additional enrollment cost associated with it are a major reason for many students to drop out (Venezia et al., 2003).

A major goal of education policy has been to leverage better student outcomes through improvements in the teacher workforce. In 1998, the Title II (Teacher Quality Enhancement Grants for States and Partnerships) legislation encouraged states to institute mandated teacher testing as part of initial state teacher certification. The No Child Left Behind (NCLB) Act of 2001 required a “highly qualified teacher” in all classrooms and public reporting of teacher qualifications.

This research focuses on how differences in high school teacher qualifications affect classroom performance. We examine differences in student achievement from teacher to teacher and assess whether some types of teachers have consistently better success in the classroom. In addition to traditional measures of teacher quality like experience and educational background, we measure whether general teacher aptitude or subject matter expertise (as measured on teacher licensure tests) are linked with better student achievement outcomes in the classroom.

The analysis relies on longitudinal data from the Los Angeles Unified School District (LAUSD). LAUSD is the 2nd largest school district in the United States with enrollment of about 700,000 students per year. We track student achievement for eight years and have student records linked to individual teachers. The dataset includes records for about 150,000 high school students per year in about 120 high schools. We focus on English Language Arts (ELA) and mathematics teachers, since students take achievement tests in these subjects each spring. LAUSD high schools employ about 2600 ELA and 1700 math teachers per year.

This study addresses the following research questions:

1. How does the distribution of teacher quality vary across high schools? A common concern is that at-risk minority students from low socioeconomic families are matched with poorly qualified teachers (Lankford et al., 2002; Murnane and Steele, 2007). In this paper, we study to what extend this is the case or if on the contrary good qualified teachers are found across schools of different composition.

2. How important are traditional measures of teacher quality like experience and educational level in predicting high school student achievement? In earlier research (Buddin and Zamarro, 2009a; Buddin and Zamarro, 2009b), we found that these measures had little effect on student achievement in elementary or middle school. High school instruction is more specialized, so more experienced or better educated teachers may have better student gains than other teachers.
3. Are teachers with higher general aptitude or more subject-matter expertise, as measured on teacher licensure tests, more successful improving student achievement than other teachers? The conventional wisdom is that high school teachers would perform better if they had a strong subject area background (National, 2004).
4. Does ELA instruction spill over into math and visa versa? For example, we will examine whether ELA teachers have an indirect effect on math achievement even after controlling for a student's math teachers. A "good" teacher in one subject may improve student engagement and learning in other subjects as well.

We structure the rest of the paper in the following way. Section 2 reviews prior literature on teacher quality and licensure test scores emphasizing the research on high school student achievement. Section 3 describes the data set and econometric methods used in the analysis. Section 4 presents the empirical results. The final section draws conclusions and makes policy recommendations.

2. Prior Literature

Teacher quality research has become increasingly sophisticated over the past twenty years as data quality has improved. Initial studies relied on cross sectional data that were often aggregated at the level of schools or even school districts (Hanushek, 1986). This approach related average school test scores to aggregate measures of teacher proficiency. Hanushek (1986) showed that most explicit measures of teacher qualifications like experience and education had little effect on student achievement.

In the 1990's, several studies looked at teacher quality issues using nationally representative samples of high school students. These studies examined whether gains in student achievement during high school were related to differences in the characteristics of their teachers. Ehrenberg and Brewer (1995) found that the teacher test scores on a verbal aptitude test were associated with higher gains in student scores although the results varied by school level and students' racial/ethnic status. Similarly, Rowan et al. (1997) found that teachers' responses to a one-item measure of mathematics knowledge were positively and significantly related to students' performance in mathematics, suggesting that teacher scores on subject matter tests may relate to student achievement as well.

In the past decade, several studies (Rivikin et al., 2005; Boyd et al., 2006; Harris and Sass, 2006; Clotfelter et al., 2007; Goldhaber, 2007; Koedel & Betts, 2007) have estimated teacher effectiveness using student administrative data, but most have focused on elementary school students. A common theme across many of these studies is that students consistently do much better with some teachers than with others, but student achievement varies little with the observed characteristics of teachers. New teachers have more difficulties than experienced teachers, but the experience effect generally dissipates after the first few years of teaching. Most teacher characteristics and qualifications have little effect on student achievement, i.e., those factors that are statistically significant generally have effect sizes of around 0.02 to 0.04. However, few studies include teacher licensure scores in their analysis. Exceptions are Clotfelter et al. (2007) and Goldhaber (2007) who found small positive effects of licensure scores on student achievement.

In our prior work (Buddin and Zamarro, 2009a; Buddin and Zamarro, 2009b), we find that teacher qualifications have little effect on student achievement of elementary and middle school students in LAUSD. We also find that measures of teacher aptitude, pedagogy knowledge, and subject-matter expertise are unrelated to student achievement for these students.

Few recent studies have examined how teacher quality affects high school student achievement. Aaronson et al. (2008) looks at teacher quality and student achievement in Chicago public high schools. The study looks at test score gains between 8th and 9th grades with controls for teacher fixed effects. The results show strong effects of teachers on student achievement with an effect size of about 0.20, but traditional measures of teacher qualifications like education, experience, and credential type have little effect on classroom results.

Koedel (2009) also used a fixed effects approach to look at student achievement for students in grades 8 through 11. He focuses on a standardized reading test given to all students at the completion of each grade. A novel feature of his approach is the control for possible spillover effects on student achievement from math, science, and social science teachers as well as the students reading (English) teacher. He finds large differences in student achievement across reading teachers, i.e., some teachers have consistently larger improvements in their classroom than others. In addition, he finds that indirect spillover effects from math teachers are nearly as important as those of the direct effect on reading achievement from the reading teacher.

Clotfelter et al. (2008) use a cross-subject fixed effects approach to estimate how teacher quality affects high school student achievement. These authors use North Carolina data where high school students are not tested in the same subject in successive years, but they are tested in different subjects instead (algebra; economic, legal, and political systems; English I, geometry, and biology) during 9th and 10th grades. As in most value-added studies of teacher quality the authors use fixed effects to control for persistent student characteristics with the additional assumption that general ability is fixed across subjects for each student. Then the authors compare how teacher qualifications affect student achievement conditional on each grade and subject. As in the other studies described below, they find that teacher experience matters only for new teachers and teacher education had no effect on achievement. Teacher licensure scores are found to be positively related with achievement, but their effect size is small (about 0.03).

3. Econometric Methods and Data

Modeling Issues

An education production function is the underlying basis for nearly all recent studies of student achievement. These modeling approaches link the current student achievement level to current family, teacher, and school inputs as well as to inputs provided in previous time periods. Following Todd and Wolpin (2003), let T_{it} be the test score measure of student i that is observed in year t and ε_{it} be a measurement error, and let X_{it} and v_{it} represent observed and unobserved inputs for student *i* at time *t.* Finally, let μ_{i0} be the student's endowed ability that does not vary over time. Assume that the cognitive production function is linear in the inputs and in the unobserved endowment and that input effects do not depend on the child's age but may depend on the age at which they were applied relative to the current age. Then, a general cognitive production function will be given by:

$$T_{it} = \mu_{i0} + \alpha_1 X_{i\,t} + \alpha_2 X_{it-1} + \ldots + \rho_1 v_{i\,t} + \rho_2 v_{it-1} + \ldots + \varepsilon_{it} \tag{1}$$

where test scores in a given year are a function of current and past observed and unobserved inputs as well as of the initial ability of the child.

Estimation of Equation 1 requires a comprehensive history of all past and present family and school/teacher inputs as well as information about each student's endowed ability. Several empirical problems complicate the estimation of this complete, ideal model:

- Endowed ability (μ_{i0}) or some student inputs are not observed, and observed student inputs maybe chosen endogenously with respect to them (student unobserved heterogeneity). For example, English learner status (an observed variable) may be correlated with family wealth (an unobserved variable). If so, the estimated effect of English learner status may reflect the underlying wealth effect in addition to the direct effect of being an English learner.
- Data sets on teacher inputs are incomplete, and observed teacher inputs maybe chosen endogenously with respect to the unobserved teacher inputs (teacher unobserved heterogeneity). For example, teacher effort may be difficult to measure, and effort might be related to measured teacher qualifications, i.e.,

teachers with higher licensure test scores may regress to the mean with lower effort.

- Students and teachers are not allocated randomly into schools or classrooms. Families with higher preferences for schooling will try to allocate their children in better schools or classrooms, principals may not allocate teachers to classrooms randomly, and good teachers may have more negotiation power to locate themselves into schools or classrooms with higher achieving students. These choices will lead to endogeneity of observed inputs with respect to unobserved student and teacher inputs or endowments.

Different specifications have been proposed in the most recent literature to try to overcome previous data limitations.

In this paper, we estimate a dynamic panel data model that includes student and teacher fixed effects in the following reduced form:

$$Y_{it} = Y_{it-1}\beta_0 + x_{it}\beta_1 + u_i\eta + q_j\rho + \alpha_i + \phi_j + \varepsilon_{it} \tag{2}$$

where Y_{it} is either the English Language Arts (ELA) or math test score of the student i in year t; x_{it} are time-variant individual observable characteristics (classroom characteristics); u_i are time-invariant individual observable characteristics (gender, race, parent's education, special attitudes and needs); and q_j are time-invariant observable characteristics of the jth teacher (gender, licensure test scores, education, experience). We estimate the model with direct teacher effects (e.g., including math teacher fixed effects on the math achievement equation) and with both direct and indirect effects (e.g., including both math and ELA teacher fixed effects on the math achievement equation). Finally, ε_{it} contains individual and teacher time variant unobserved characteristics.[1,2]

Both teachers and students enter and exit the panel so, we have an unbalanced panel. Students also change teachers (generally from year to year). This is crucial, because fixed effects are identified only by the students who change teachers. It is assumed that ε_{it} is strictly exogenous. That is, student's assignments to teachers are independent of ε_{it} . Note, according to this assumption, assignment of students to teachers may be a function of the observables and the time-invariant unobservables.

It is usual to assume that the unobserved heterogeneity terms (α_i and ϕ_j) are correlated with the observables (due to student unobserved heterogeneity, teacher unobserved heterogeneity and non-random assignment of students to teachers). Thus, random effect methods are inconsistent, and fixed effect methods are needed. In this case, the coefficients of students and teachers' time invariant observed characteristics (ρ and η) are not identified separately from the unobserved heterogeneity terms. Given that the objective of this paper is to asses the role of such observed teacher characteristics on determining student performance, rather than dropping the variables u_i and q_j, we define:

$$\psi_j = \phi_j + q_j\rho \qquad (3)$$

$$\theta_i = \alpha_i + u_i\eta \qquad (4)$$

Then, we estimate the models in two steps. In a first step we estimate the following equation using fixed effects methods:

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[1] We discuss modeling issues in more detail in our earlier paper on student achievement in elementary school (See Buddin and Zamarro, 2009a).

[2] We also estimated fixed effects levels model assuming β_0=0 and a gains model assuming β_0=1. We prefer the more general model in Eq. 2, because it incorporates a more flexible adjustment for student heterogeneity. The teacher effects from the dynamic panel model are similar to those for the more restrictive levels and gains models.

$$\mathrm{Y}_{\mathrm{it}} = \mathrm{Y}_{\mathrm{it}-1}\,\beta_0 + \mathrm{x}_{\mathrm{it}}\beta_1 + \theta_i + \psi_j + \varepsilon_{\mathrm{it}} \tag{5}$$

Then, in a second-stage regression we evaluate the ability of a rich set of observable teacher qualifications to predict teacher quality (ψ_j). Many of the observable teacher characteristics considered in this analysis are important determinants of teacher recruitment, retention and salaries decisions. In the same manner, we also analyze the ability of observable student characteristics to predict the student ability term (θ_i). Causal interpretation of the coefficients in these second step regressions would need the additional assumptions that Cov(u_i, α_i)=Cov(q_j, ϕ_j)=0. As explained below, this assumption is unlikely to be satisfied in this context. Thus, our second step estimates should not be interpreted as causal effects but as measures of the correlation between observed characteristics and the teacher quality and student ability terms. Finally, our dependent variables in these second step regressions are statistical estimates of the true measures of teacher quality and student ability (ψ_j and θ_i) and as such they are measured with error. Thus, to obtain efficient estimates of the parameters we perform Feasible Generalized Least Squares (FGLS) regressions where the weights are computed following Borjas (1987).

A practical problem in estimating equations (5) is that there is no straight forward algebraic transformation of the observables that allow us estimate these equations and easily recover the estimates of the students and teachers' fixed effects.[3] Abowd et al. (1999), in an application for employer- employee data, propose to explicitly including dummy variables for employer heterogeneity and sweeping out the employee heterogeneity algebraically. They proved that this approach gives the same solution as the

[3] See Abowd et al (1999) for a description of suitable methods to estimate models with two levels fixed effects in the context of linked employer-employee data.

Least Squares Dummy Variables estimator for fixed effects panel data models. However, this method leads to computational difficulties because the software needs to invert a (K+J)×(K+J) matrix and store a lot of information. K refers to the total number of explanatory variables while J is the total number of teachers. Thus, we estimate the models in equations (5) using a preconditioned conjugate gradient method described in Abowd, Creecy & Kramarz (2002).[4] Guimaraes and Portugal (2009) proposed an alternative approach to estimation using a simple to implement iterative procedure that can be easily extended to alternative specifications of the model.

In addition to previous computational difficulties, estimation of equation (5) has the additional complication that taking differences to eliminate the student fixed effects will lead to correlation of the differenced lagged score ($Y_{it-1} - Y_{it-2}$) and the differenced error term ($\varepsilon_{it} - \varepsilon_{it-1}$). Anderson and Hsiao (1981) proposed using an instrumental variable estimator with Y_{it-2} as an instrument for ($Y_{it-1} - Y_{it-2}$). This is a valid method since Y_{it-2} is not correlated with ($\varepsilon_{it} - \varepsilon_{it-1}$), assuming the errors are not serially correlated. This is the approach we follow to obtain estimates of equation (5). In particular, we follow Guimaraes and Portugal (2009) proposed routine for estimating models with high dimensional fixed effects and obtain instrumental variable estimates of equation (5) using Y_{it-2} as instrument.[5]

[4] Amine Ouazad developed the STATA routine used for the estimation of equation (5). The software is available on the web at http://repository.ciser.cornell.edu/viewcvs-public/cg2/branches/stata/.
[5] An alternative more efficient estimator method uses additional lags of the dependent variable as instruments (see Arellano and Bond (1991)). The model is then overidentified, so estimation should be by 2SLS or GMM methods. Given to computational difficulties derived from combination of these methods with high dimensional fixed effects we are not able to obtain estimates using these alternative methods.

Other potential data problems include, sample selection and attrition. Sample selection is due to the fact that we only observe teachers who passed their licensure exams. Although we acknowledge that the results we obtain are not representative for the whole population of potential teachers, they are for those teachers who are deemed eligible to teach. In this sense, we still believe the estimates we obtain in this population are the most relevant ones because these are the teachers who effectively will be participating in the educational system. On the other hand, literature suggests that more qualified teachers are more likely to leave the profession sooner (See e.g. Goldhaber, 2007). This phenomenon constitutes another source of potential bias. As a specification check, we estimated our models for teachers with less than 6 years of teaching experience, and the results did not differ from the ones for the whole sample. As a result, only the results corresponding to the complete sample are presented in the next sections.

Some students dropout of high school, so we observe student test score only for high school grades completed by each student. If this sample attrition is due to either observed or unobserved time-invariant student characteristics, then the model estimates will be consistent (Cameron and Trivedi, 2005). As a further check for attrition bias associated with dropouts, we reestimated the model using inverse probability weights to adjust for the probability of each student dropping out in each year. The weighted estimates were similar to the unweighted estimates, and the correlation between teacher effects in the two models was over 0.90. As a result, we focus on the unweighted estimates in the results section below.

Data

Student Achievement and Teacher Data

As in the rest of the country, California high school students have low graduation rates and many graduates are unprepared for college. About 80 percent of high school students graduate and 34 percent of graduates meet course requirements for attending a California four-year public college.[6] Urban high school students fare worse than students in suburban and rural schools. About 72 percent of Los Angeles Unified School District (LAUSD) high school students graduate and 26 percent of graduates have completed college required courses. Within LAUSD, African American and Hispanic students fare much worse than white, non-Hispanic students. The graduation rates are 57, 64, and 79 percent for African American, Hispanic, and white non-Hispanic students, respectively. Similarly, 22 percent of African American and Hispanic graduates meet course requirements for college as compared with 37 percent of white non-Hispanic students.

About 85 percent of high schools in LAUSD are Title I schools, since over 40 percent of their students are from low income families. These schools received special categorical funding from the federal government to improve the achievement of disadvantaged students. Title I schools are designated at Program Improvement (PI) schools if they fail to make adequate yearly progress towards meeting state achievement standards for two consecutive years. Under PI, NCLB requires schools to provide various options to parents including transfers to other schools, supplemental educational services for students, and restructuring. In 2007 (see Figure 3.1), 85 percent of LAUSD high

[6] High school dropout rates are difficult to measure, since districts have limited information about whether students leaving their district enroll in another district (Swanson, 2008; Greene and Forester, 2003). The California dropout rate is based on student-level data using the California Department of Education's statewide student identifier. The new system allows the longitudinal tracking of students from district to district in the state and is more accurate than the earlier system were some intrastate transfers were counted as dropouts. Without the recent longitudinal tracking, Greene and Forester (2003) had estimated the California dropout rate as 33 percent for the public high school class of 2001.

schools were Title I schools. Among the Title I schools, half are in Program Improvement (PI) status. About 20 percent of Title I schools have been in PI for 5 or more years.

Table 3.1 describes the characteristics of LAUSD high school students. About 70 percent of students are Hispanic and 28 percent are English Language Learners (ELLs). About 37 percent of Hispanics are ELLs as compared with 7 percent of other students. Two-thirds of students come from low income families eligible for free/reduce school lunches of the federal government. Parental education levels in the district are also low and provide further indication of disadvantages faced by many students in the district.

Student achievement is measured on the California Standards Test (CST), in reading and math. The CST is aligned with state curriculum standards and reflects the material covered in the respective high school courses. CST raw scores are normalized by grade and year, so our models are based on a continuous linear scale.

Table 3.2 shows that students and teachers are unevenly spread across schools in the district. As in most urban areas, wealth varies across neighborhoods in the districts and the composition of neighborhood schools reflects these differences. The table shows the student and teacher composition of schools in the bottom and top achievement quartile. Schools in the bottom quartile have test scores nearly a standard deviation lower than those in the top quartile. Low performing students have large concentrations of black, Hispanic, and ELL students. About 51 percent of students in low performing schools have parents with less than a high school diploma as compared with only 23 percent of students in the top quartile.

The distribution of teacher characteristics also varies substantially between low- and high-achievement schools. Teachers in the bottom quartile have less experience than in the top quartile, and they are much more likely to be black or Hispanic. Teacher licensure scores are around 0.5 to 0.7 standard deviations lower at low-achievement schools than at high-achievement schools. The teacher assignment pattern mirror that reported by Lankford et al. (2002) in New York City and substantiates the assertion that low-income and at-risk students are often match with teachers with weak qualifications as measured by traditional criterion (Murnane and Steele, 2007).

An important data issue is how schools sort students into classes. If student assignments were based on prior achievement or achievement trajectory, then naïve measures of teacher effects might be misleading. For example, if a subset of teachers at each school consistently received the "best" students (based on their prior ability), then these teachers would have a head start for having high-achieving students at the end of the year. Two factors minimize the importance of school level sorting. First, student achievement scores from spring testing are not available until late summer when class assignments are already determined. Second, the dynamic panel data model controls for various types of student sorting by controlling for student heterogeneity through prior test scores and through student fixed effects.

We show the extent of student sorting within high schools in Table 3.3. The table entries show the mean standard deviation in prior student test scores for each teacher under various sorting scenarios. The levels column indicates the average prior test score of students for each teacher, and the gains column indicates the average change in test score for the prior two years for each teacher. With random sorting, the standard deviation for each teacher would be relatively large, because each teacher would have a mixture of students with low- and high-prior test scores. Alternatively, with perfect sorting, each teacher would have a relatively homogeneous mix of students, and the standard deviation of prior scores would be small.

The results in Table 3.3 suggest that sorting effects in LAUSD are small.[7] The observed within school pattern of assignment is much closer to random than perfect assignment for all grades in both ELA and math. The gaps between the random and observed entries are smaller in math than in reading and much smaller in the gains model than in the levels model. The evidence indicates that sorting is not a major issue for LAUSD students.

Teacher Licensure Data

The California Commission on Teacher Credentialing (CCTC) requires teachers to pass two tests for a secondary-level teaching credential.[8] The California Basic Educational Skills Test (CBEST) is given to teacher candidates before they enter teacher preparation programs. The test measures general aptitude in reading, writing, and math. Teaching candidates must also pass the appropriate California Subject Examination for Teachers (CSET) test in each subject that they are certified to teach. We focus on teachers certified in English and mathematics, since ELA and mathematics are the primary subjects tested in California's student achievement tests.[9]

All teacher candidates must take the general aptitude test. The first-time pass rates are 81 percent for white non-Hispanic teaching candidates but only 44 and 53 percent for Black and Hispanic candidates (Jacobson and Suckow, 2006). After retesting, the pass

[7] Aaronson et al. (2007) and Koedel (2009) use similar measures of student sorting for Chicago and San Diego high school districts. They also find small levels of student sorting in their studies.
[8] Le and Buddin (2005) provides more detail on how the tests are constructed and assessed validity evidence for the tests.
[9] Students are also tested in other areas like social sciences and sciences, but these tests are not given to student in successive grades. We focus on ELA and math, because repeated observations in each subject in needed for the value-added approach described above.

rates increase substantially, and the race/ethnic gap in pass rates narrows considerably. This suggests that many candidates may improve their skills and preparation to meet the pass criterion or test familiarity boosts scores. The cumulative pass rates are 93, 69, and 77 for white non-Hispanics, Blacks, and Hispanics, respectively. Many candidates may be discouraged by failing one of the tests, however, and lose interest in teaching.

The first-time pass rates on CSET English test are 66 percent for white non-Hispanics as compared with 36 and 49 percent for black and Hispanic candidates (Jacobson and Suckow, 2006). The cumulative rate is about 10 percentage points higher for white non-Hispanic and Hispanic candidates, while the cumulative pass rate for blacks is 56 percent.

The first-time pass rates for math are low, and the cumulative rates are not much higher (Jacobson and Suckow, 2006). Initial pass rates are 22, 29, and 44 percent for blacks, Hispanics, and white non-Hispanics, respectively. The cumulative rates for each group are only about 3 percentage points higher than the initial pass rates.

Pass rates on both CBEST and CSET are positively correlated with other measures of student skills. The CBEST pass rate for "A" students is nearly 20 percentage points higher than for "B" students. Similarly, the CSET English and math pass rates are 20 percentage points higher for "A" than for "B" students.

Teacher licensure scores are collected by the CCTC through the teacher accreditation process, but they are not available to either school districts or teaching candidates. We worked with the California State University Chancellor's Office to obtain licensure tests for seven cohorts of CSU teaching candidates. The file includes licensure scores for about 62,000 teaching candidates from 2000 through 2006. Separate scores are recorded on a basic skills test and each subject area test. The file contains information on failed exams, so we know whether a teacher needed to retake one or more exams as part of the certification process.

The CSU licensure data are available for around 18 per cent of the LAUSD high school teachers. This low match rate reflects two key factors. First, most teachers in the district received their certification before 2000 and have been teaching for some time. The match rate rises to around 23 percent for teachers in their first three years of teaching. Second, CSU only has access for licensure scores for candidates from their various campuses and not from the entire state. About 50 percent of California teaching certificate completers are affiliated with a CSU campus. We were unable to obtain additional licensure information from either the California Commission on Teacher Credentialing or other campuses.

Several different methods were used in the empirical analysis to handle the missing information on licensure test scores. In each approach, stage 1 regressions are estimated as described above on the entire sample. The adjustment for missing licensure data occurs in stage 2 using data on estimated teacher effects in reading and math.

- Multiple imputation. This approach imputes licensure scores from other teacher characteristics and estimated teacher effects in reading and math. Multiple datasets are created with different imputed values, and final parameters estimates are blended from regressions on each dataset. The methods rely on assumptions such as Missing at Random or Missing Completely at Random that are made on the conditional distributions of the licensure score variables.[10] We are concerned

[10] See, e.g., Rubin (1996) for a description of Missing at Random and Missing Completely at Random assumptions and their application in imputing methods.

that this approach is not well suited to our situations where we have large proportions of missing variables, and we would rather prefer not to make assumptions about their (conditional) distributions.

- Dropping records with missing teacher data. In this approach, we estimate stage 2 entirely on matched CSU teachers. The results show whether licensure scores for recent CSU teaching graduates are significantly related to student achievement in each teacher's classroom. We are concerned that this approach focuses on the CSU sample of young teachers and ignores the other teachers. The broader group of teachers would provide more information on how other teacher characteristics affect student achievement.
- Missing dummy variables. A common missing value adjustment consists of setting the value of the missing covariate to an arbitrary fixed value (zero) and, adding dummy variables for "missings."

The main analysis results reported below rely on the missing dummy variable approach. We also estimated various models with the missing multiple imputation and "dropped records" approaches, and these results were similar to those reported below.

4. Results

Distribution of Teacher Quality Across Schools

A key policy issue is whether "good" teachers are concentrated in a few high schools or spread across the district? Table 3.2 showed that nominal teacher qualifications differed substantially between low- and high-achieving high schools. What is unclear from the table, however, is how those teacher qualifications translate into student achievement outcomes in the classroom. If teachers with better qualifications are consistently improving achievement more than other teachers, then student achievement changes from year to year should mirror the differences reported in Table 3.2

We tested for differences in teacher effects across high schools by comparing teacher effects from school to school. If teacher quality was relatively homogeneous within schools, then the differences in outcomes across schools after controlling for student fixed effects would be larger than the differences across teachers. Alternatively, if teacher quality varied substantially within schools, then cross school differences would be smaller than across teachers, because low- and high- quality teachers within schools would lower the differences across schools.

Table 4.1 shows the pattern of fixed effects across students, teachers, and schools, based on a simple model that only accounts for grade and year effects. As expected, the results show that student-to-student differences are the largest component of effects reflecting differences in student background and preparation. The gains models show a similar pattern where student effects are much larger than either teacher or school effects.

The teacher and school effects in Table 4.1 show that high quality teachers are not concentrated in a few schools. Deviations in teacher effects are larger than school effects across both ELA and math scores in both the levels and gains models. This pattern occurs because high quality teachers as measured by either levels or gains are dispersed across schools. School fixed effects are smaller than teacher fixed effects, because schools include combinations of teachers with differing effects on student outcomes.

By implication, the results in Table 4.1 suggest that the nominal measures of teacher quality that differ widely from school to school may be weak measures of how well teachers do in the classroom. We examine this in more detail below, but this simple model hints that difference in teacher effects across schools are smaller than are difference in nominal measures of teacher qualifications.

Estimates of Value-Added Models

We estimated two versions of the student achievement model in equation (5) for student achievement in both ELA and math. The first version focuses on the separate, direct effect on student achievement of a teacher in the same subject (e.g., the effect of a student's math teacher on their math achievement). The second version is a joint model controlling for both direct and indirect effects of teachers on student achievement (e.g., the effect of a student's math and ELA teacher on their math achievement). The premise of the second model is that a good teacher in another subject may have some indirect effect on achievement perhaps by improving general student skills or focus on learning.

In addition to teacher and student effects, the models also control for the composition of each student's class and student/teacher matches.[11] As explained in previous sections, the central problem with estimating the effect of these peer and match variables is that families may self-select their children into classrooms and schools depending on their children ability. Moreover, schools may assign their teachers to a given classroom depending on its composition. As a result, these variables are potentially endogenous. This is taken into account in our estimates including both student and teacher fixed effects allowing for correlation between them and the explanatory variables.[12]

[11] The models also contain controls for student grade and year.

[12] Most of the research on peer effects dealt with selection by controlling for observable variables, comparing siblings that experienced different schools, examining desegregation programs or estimating selection models (Angrist & Lang, 2002). Other parts of the literature exploit the availability of policy or natural experiments to estimate peer effects (Zimmerman, 1999 and Sacerdote, 2000). Hoxby (2000) exploits the variation in adjacent cohorts' peer composition within a grade within a school that is idiosyncratic to estimate peer effects. Cullen and Jacob (2007) use lottery data to look at open enrollment

The results differ somewhat between ELA and math, but they are similar for the separate and joint teacher effects models. The results in Table 4.2 show a small positive effect of class size on student achievement. Several measures of peer effects are statistically significant, but the magnitude of the effects is small. The proportion of girls in the class is positively related to ELA achievement and inversely related to math achievement. If we increase the proportion of girls from 0.5 to 0.6, we would increase individual achievement in ELA by only 0.003 standard deviations and reduce individual math achievement by only 0.006 standard deviations. ELA and math achievement is low in classes with larger shares of black students. The Hispanic class share generally has no significant effect on either type of achievement. Asian composition has no effect on reading achievement and a negative effect on math achievement. The proportion of ELLs in a class is inversely related to ELA achievement and positively related to math achievement.

Previous research by Dee (2005), Clotfelter et al. (2007), and Ouazad (2007) find that students do better academically when they are matched with a teacher of similar race/ethnicity or gender. We find that female students do better when matched with female teacher—the effect size is less than 0.01 in ELA, but it is five times larger in math. Hispanic students do slightly better when taught by a Hispanic math teacher (0.02 effect size) and slightly worse when taught by a Hispanic ELA teacher (0.01 effect size). Black students have math achievement 0.02 standard deviations lower with a black teacher and no different ELA achievement. Asian/Pacific Islander students do benefit

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effects for Chicago elementary school students. They find lottery winners are matched with higher quality peers in their new schools but their subsequent achievement scores are not higher than those of lottery losers.

from being matched with a similar teacher in math, where the effect size is about 0.9. We hypothesized that higher SES students might benefit more from teachers with more education than other students. The results show that students with college parents have neither higher nor lower achievement levels when matched with a teacher with a master degree or a Ph.D.

The coefficient on the lagged test score variable is an indication of the persistence of ELA and math skills from year to year. The parameter is 0.15 in ELA and 0.39 in math. These parameter estimates are significantly different from zero as implied by the levels model and from unity as implied by the gains model. The results suggest that a dynamic panel data model is preferred to either the levels or gains model. On a practical level, however, we found similar estimates for these other models to those reported here.

The teacher effects parameters in Table 4.2 show strong teacher effects in both ELA and math. In the first model with only ELA teacher effects; a standard deviation in teacher effects is associated with a 0.18 standard deviation in ELA achievement. The magnitude of this effect falls to 0.17 standard deviations in the second model where we also control for indirect effects of the math teacher on ELA achievement. The indirect effects of the math teacher are 0.14 standard deviations even after controlling for the ELA teacher. We found only a small correlation of 0.04 between the ELA and math teacher effects, so the direct and indirect teacher effects are operating independently of one another. Also, the small correlation between teacher effects suggests that students are not systematically sorted by both types of teachers.

Differences in math teacher effects are larger than those for ELA. Looking at the math teacher effects separately, we find that a standard deviation change in math teacher quality is associated with a 0.29 standard deviation in math student achievement. This effect falls to 0.25 in the joint model. In the joint model, the indirect effect of a standard deviation change in the ELA quality distribution is association with a 0.24 effect on math achievement. The correlation between the math and ELA teacher effects is 0.17. While this correlation is much higher than in ELA achievement, the direct and indirect effects are still operating somewhat independently of one another. The surprising result here is that the indirect of the ELA teacher on math achievement is almost as large as the direct effect of the math teacher on math achievement.

Teacher Quality and Observed Teacher Characteristics

Second-stage regressions were used to measure how time-invariant teacher characteristics affect student achievement. The teacher effects from the separate and joint models were highly correlated, but we estimated separate second-stage models to look for possible differences between the two models. The specifications controlled for teacher experience, gender, race/ethnicity, education level, and teacher licensure scores.

In ELA, the results show that almost none of the variables have a statistically significant effect on student achievement in either the separate or joint model. Traditional measures of teacher quality like experience and education level do not matter for ELA teachers. Similarly, ELA teachers with higher general aptitude or more subject-area knowledge have no high student achievement outcomes than other teachers.

In math, the results show that experienced math teachers have slightly lower achievement gains in their classes than less experienced teachers. Black and Hispanic teacher have achievement scores 0.06 and 0.04 standard deviations higher than white non-Hispanic teachers in the model with only math teacher effects, but these effects become statistically insignificant in the joint specification. Teacher education level has no effect on classroom outcomes. None of the teacher licensure scores has any affect on student achievement in math.

Finally, we estimated how teacher effects differed across schools in the performance quadrants as described in Table 3.2. While measured teacher characteristics varied substantially between low- and high-performing schools, we found no statistical difference in the teacher effects for these two quadrants. Teacher effects are relatively balance across high schools even although the mix of teacher qualifications is unbalanced.

5. Conclusions

The results show large differences in high school student achievement from teacher to teacher, but these differences are unrelated to measured teacher qualifications and background. These results are consistent with our earlier findings for elementary and middle school students in LAUSD (Buddin and Zamarro, 2009a; Buddin and Zamarro, 2009b) where we also found little effect of teacher characteristics on student achievement. A key issue for researchers and policymakers is to identify why some teachers are much more effective than others.

How does the distribution of teacher quality vary across high schools?

Teacher experience, education level, and licensure scores vary considerably between low- and high-achieving high schools. Disadvantaged students are concentrated in low-performing schools and are generally taught by teachers with lower *measured* quality than students in more affluent areas.

Measured teacher attributes like experience, education level, and licensure scores are largely unrelated to student achievement in the classroom, however. Many teachers in low-performing schools have student achievement gains comparable to those of teachers in high-performing schools. In terms of student outcomes, teacher quality is much more balanced across high schools than are the measured qualifications of teachers.

How important are traditional measures of teacher quality like experience and educational level in predicting high school student achievement?

We find that teacher experience and education level are largely unrelated to high school student achievement. We do find evidence that more experienced math teachers have slightly worse student outcomes than new math teachers.

Our results imply that incentives to improve the traditional qualifications of teachers at low-performing high schools are unlikely to improve educational outcomes at those schools.

Are teachers with higher general aptitude or more subject-matter expertise, as measured on teacher licensure tests, more successful improving student achievement than other teachers?

We find than neither general aptitude nor subject area knowledge of teachers has any effect on high school student achievement in the classroom. The California licensure tests include content that is consistent with the job of teaching, and the cut scores are derived in a defensible manner (Le and Buddin, 2005). While the tests do screen some teaching applicants from obtaining teaching certificates, the scores themselves do not predict how well individual teachers will perform in the classroom.

A caveat to our licensure results is that we are unable to measure how well teachers who fail the licensure tests would have done in the classroom. Perhaps candidates with lower general aptitude or subject area knowledge would have performed worse in the classroom than teachers that did pass the exams. Nonetheless, our results suggest that increasing the California licensure cut scores would do nothing to improve student achievement of high school students.

Perhaps states should rethink licensure tests and build measures of teacher skills that are better predictors of student achievement in the classroom. Different standards might restrict entry into the teacher profession, however, and have adverse consequences for teacher supply (Angriest and Ugrian, 2003).

Does ELA instruction spill over into math and visa versa?

We find that high quality teachers have important indirect effects on student achievement beyond their immediate subject area. The quality of the ELA teacher affects math student achievement even after controlling for the direct effects of the math teachers. Similarly, high quality math instruction improves the ELA achievement of high school students after controlling for the direct effects of the ELA teacher. The spillover effects suggest that teaching quality may have a broader effect on student enthusiasm or engagement that extends beyond one class and more broadly improves student achievement outcomes.

A final issue is the context for measuring teacher effectiveness. LAUSD, like most districts, bases teacher compensation on inputs like teacher experience and educational level. By California statute, teacher assessments do not include student test results, and teachers are not directly rewarded for improving student achievement.[13] Since the current compensation system rewards teacher inputs and not teacher output, teachers may have insufficient incentives to consistently provide their “best” effort in improving student achievement. Perhaps more experienced or more knowledgeable teachers could perform better than other teachers, but the current compensation scheme does not sufficiently reward the extra effort.

[13] The Obama Administration is pressuring California and other states to use student achievement results in teacher assessments. California and other states may revise their practices for reviewing teacher effectiveness to enhance their eligibility for federal education funding (Felch and Song, 2009).

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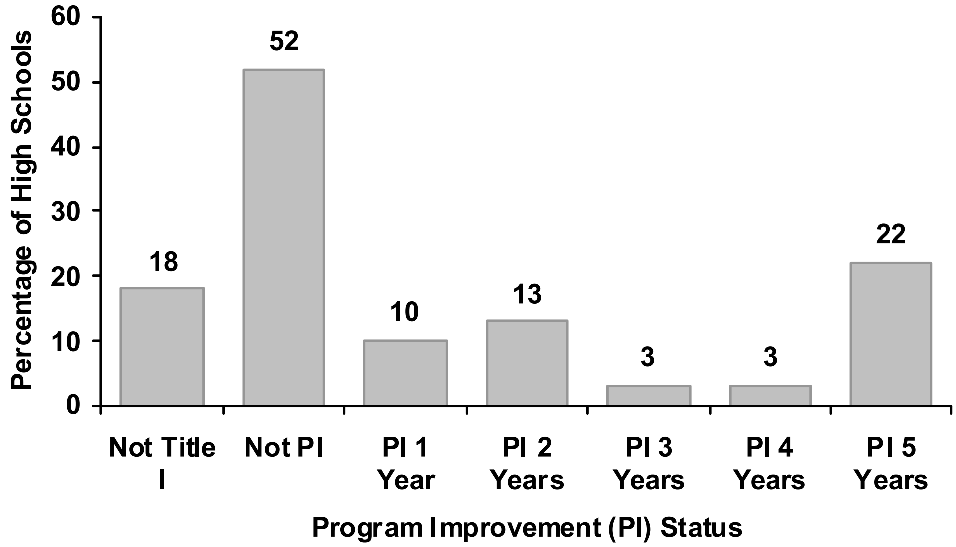

Figure 3.1—Program Improvement Status for LAUSD High Schools in 2007

Table 3.1—Characteristics of High School Students

Student Characteristics	Proportion
Black	0.13
Hispanic	0.69
Asian/Pacific Islander	0.07
Female	0.49
English Language Learner	0.28
Free/reduced lunch	0.66
Highest Parental Education	
Not high school graduate	0.35
High school diploma	0.24
Some college	0.16
College graduate	0.19
Some graduate school	0.06

Table 3.2--Comparison of Student and Teacher Characteristics in Schools with Lowest and Highest Test Scores in 2007

School Characteristics	Lowest Quartile Schools	Highest Quartile Schools
Enrollment (grades 9 through 11)	2061	1746
Student Characteristics		
ELA (Standardized)	-0.47	0.50
Math (Standardized)	-0.61	0.33
Black	0.22	0.11
Hispanic	0.77	0.54
English Language Learner	0.36	0.14
Parents Not High School Graduates	0.51	0.23
ELA & Math Teacher Characteristics		
Experience	6.81	10.78
Black	0.30	0.09
Hispanic	0.22	0.15
Master's/Doctorate	0.32	0.35
General Aptitude (Standardized)	-0.10	0.39
ELA Subject Matter Knowledge (Standardized)	-0.30	0.28
Math Subject Matter Knowledge (Standardized)	-0.22	0.54

Table 3.3. Mean Standard Deviation of Incoming Student Test Scores by Teacher

	ELA		Math	
	Level	Gain	Level	Gain
9th Grade				
Random Sorting	0.89	0.57	0.99	0.75
Observed	0.76	0.57	0.90	0.74
Perfect Sorting	0.20	0.16	0.29	0.27
10th Grade				
Random Sorting	0.89	0.60	0.91	0.88
Observed	0.73	0.60	0.81	0.84
Perfect Sorting	0.20	0.18	0.27	0.28
11th Grade				
Random Sorting	0.86	0.58	0.80	0.82
Observed	0.70	0.58	0.68	0.79
Perfect Sorting	0.29	0.17	0.25	0.26

Notes: Entries are based on standardized test scores by teacher within each school.

Table 4.1—Comparison of Student, Teacher, and School Fixed Effects

	Levels		Gains	
	ELA	Math	ELA	Math
#1. Student & Teacher Fixed Effects				
Student ($\sigma_{Student}$)	0.93	0.85	0.47	0.58
Teacher ($\sigma_{Teacher}$)	0.11	0.15	0.13	0.24
#2. Student & School Fixed Effects				
Student ($\sigma_{Student}$)	0.94	0.84	0.46	0.56
School (σ_{School})	0.08	0.11	0.09	0.14

Table 4.2. Effects of Class Characteristics and Student/Teacher Match on High School Student Achievement with Student and Teacher Fixed Effects

	ELA Achievement		Math Achievement	
	ELA Only	ELA & Math	Math Only	Math & ELA
Lagged Test Score	0.1528*	0.1575*	0.4365*	0.3896*
	(0.0061)	(0.0053)	(0.0089)	(0.0087)
Class Size	0.0012*	0.0012*	0.0011*	0.0010*
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Proportion Female in Class	0.0337*	0.0334*	-0.0594*	-0.0630*
	(0.0088)	(0.0080)	(0.0180)	(0.0140)
Proportion Black in Class	-0.0543*	-0.0541*	-0.0886*	-0.0751*
	(0.0131)	(0.0139)	(0.0327)	(0.0319)
Proportion Hispanic in Class	-0.0156	-0.0167	-0.0482*	-0.0335
	(0.0102)	(0.0091)	(0.0244)	(0.0252)
Proportion Asian/Pacific Islander in Class	-0.0104	-0.0104	-0.3171*	-0.2984*
	(0.0150)	(0.0130)	(0.0430)	(0.0334)
Proportion ELL in Class	-0.0344*	-0.0346*	0.0136	0.0257*
	(0.0048)	(0.0040)	(0.0098)	(0.0086)
Hispanic Student & Teacher	-0.0077*	-0.0079*	0.0186*	0.0167*
	(0.0030)	(0.0024)	(0.0065)	(0.0052)
Black Student & Teacher	0.0118	0.0117	-0.0270*	-0.0279*
	(0.0067)	(0.0061)	(0.0111)	(0.0092)
Asian/Pacific Islander Student & Teacher	-0.0166	-0.0173	0.0981*	0.0913*
	(0.0120)	(0.0090)	(0.0181)	(0.0145)
Female Student & Teacher	0.0073*	0.0075*	0.0547*	0.0514*
	(0.0027)	(0.0024)	(0.0043)	(0.0040)
College Parents & Teacher Masters/Ph.D.	0.0042	0.0045	0.0110	0.0095
	(0.0035)	(0.0028)	(0.0075)	(0.0094)
Constant	-0.0591*	-0.0046*	-0.1515*	-0.0003
	(0.0018)	(0.0014)	(0.0070)	(0.0041)
σ_{Math}		0.1391	0.2881	0.2507
σ_{ELA}	0.1822	0.1710		0.2446
σ	0.6520	0.6410	1.0701	1.0253
ρ_{Math}		0.0471	0.0725	0.0594
ρ_{ELA}	0.0781	0.0693		0.0569
R-Squared	0.0017	0.0187	0.1172	0.1296
N	457385	457385	435608	435608

* $p<0.05$

Table 4.3. Effects of Teacher Qualifications on High School Student Achievement

	ELA Achievement		Math Achievement	
	ELA Only	ELA & Math	Math Only	Math & ELA
Experience	0.0017	0.0015	-0.0091*	-0.0057*
	(0.0012)	(0.0011)	(0.0022)	(0.0018)
Experience Squared	-0.0000	-0.0000	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Female	0.0029	0.0039	0.0028	0.0116
	(0.0067)	(0.0063)	(0.0125)	(0.0098)
Black/African American	-0.0124	-0.0053	0.0604*	0.0218
	(0.0103)	(0.0096)	(0.0189)	(0.0150)
Hispanic	0.0199*	0.0118	0.0378*	0.0075
	(0.0089)	(0.0084)	(0.0160)	(0.0125)
Asian/Pacific Islander	0.0146	0.0124	0.0077	0.0032
	(0.0128)	(0.0120)	(0.0169)	(0.0131)
Masters	-0.0018	-0.0061	0.0144	0.0156
	(0.0074)	(0.0070)	(0.0150)	(0.0118)
Ph.D.	-0.0074	-0.0034	-0.0166	0.0033
	(0.0196)	(0.0184)	(0.0389)	(0.0301)
General Aptitude Score	-0.0084	-0.0043	-0.0211	-0.0165
	(0.0090)	(0.0084)	(0.0161)	(0.0127)
English Score	0.0020	0.0002		
	(0.0176)	(0.0165)		
Math Score			-0.0229	-0.0190
			(0.0302)	(0.0234)
Constant	-0.0809	-0.0828	-0.0958	-0.0362
	(0.0638)	(0.0599)	(0.1151)	(0.0903)
R-Squared	0.0019	-0.0007	0.0360	0.0185
N	3164	3164	2017	2017

* p<0.05