EFFECTIVE SCHOOLS: TEACHER HIRING, ASSIGNMENT, DEVELOPMENT, AND RETENTION

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Abstract

The literature on effective schools emphasizes the importance of a quality teaching force in improving educational outcomes for students. In this article we use value-added methods to examine the relationship between a school's effectiveness and the recruitment, assignment, development, and retention of its teachers. Our results reveal four key findings. First, we find that more effective schools are able to attract and hire more effective teachers from other schools when vacancies arise. Second, more effective schools assign novice teachers to students in a more equitable fashion. Third, teachers who work in schools that were more effective at raising achievement in a prior period improve more rapidly in a subsequent period than do those in less effective schools. Finally, we find that more effective schools are better able to retain higher-quality teachers. The results point to the importance of personnel and, perhaps, school personnel practices for improving student outcomes.

1. INTRODUCTION

The literature on effective schools emphasizes the importance of a quality teaching force in improving educational outcomes for students. The effect of teachers on student achievement is well established. Quality teachers are one of the most important school-related factors found to facilitate student learning (Nye, Konstantopoulos, and Hedges 2004; Rockoff 2004). Not all schools are able to attract and retain the same caliber of teachers (Lankford, Loeb, and Wyckoff 2002). Teacher preferences for student characteristics and school location explain some of the sorting (Boyd et al. 2005; Hanushek, Kain, and Rivkin 2004; Scafidi, Sjoquist, and Stinebrickner 2008); however, school personnel practices are also likely to play an important role. Schools can control the quality of their teaching force through at least three mechanisms: recruiting quality teachers, strategically retaining quality teachers (and removing low-quality teachers), and developing the teachers already at their school. In addition, they can allocate teachers more or less effectively across classrooms. In this article we examine the extent to which more effective schools are better able to recruit, assign, develop, and retain effective teachers and remove less effective teachers.

To examine the relationship between school effectiveness and teachers' careers, we use seven years of administrative data on all district staff and students in one of the largest public school districts in the United States, Miami-Dade County Public Schools (M-DCPS). From these data we generate measures of school and teacher value added and use these two effectiveness measures to better understand the importance of personnel practices. Our results reveal four key findings. First, among teachers who switch schools, higher value-added elementary schoolteachers transfer to schools with higher school-level value added. Second, more effective schools provide more equitable class assignments to their novice teachers. Novice teachers in more effective schools receive students with similar average prior achievement to their colleagues, which is not the case in less effective schools. Third, more effective schools are better able to develop their teachers' ability to raise student achievement. Teachers' value added improves more between years when they work in schools that were more effective in a prior period. Fourth and finally, we find that more effective schools are better able to retain effective teachers. Teachers who are in the top quartile of teacher value added are substantially less likely to leave when employed in more effective schools than when employed in less effective schools.

2. BACKGROUND

Although academic ability and family backgrounds of students are important determinants of achievement, schools with similar student profiles can vary widely in the learning gains of their students (Sammons, Hillman, and Mortimore 1995; Willms and Raudenbush 1989). A huge body of research, often termed the Effective Schools Research, has sought to understand why some schools are more effective than others (see Jansen 1995 and Purkey and Smith 1983 for examples of the many reviews). In this article we define effective schools in a way similar to much of this prior literature as schools in which students learn more than expected, given their background characteristics, over the course of a school year (e.g., Mortimore 1991). However, unlike much of the early Effective Schools Research, our study is based on an analysis of a range of schools in a given geographic area, not solely on case studies of more or less effective schools. By using detailed and linked longitudinal data on students, teachers, and schools, we are able to build upon this earlier research on school effectiveness using more rigorous statistical approaches to examine the extent to which personnel practices distinguish more and less effective schools.

Quality teachers are one of the most important school-related factors found to facilitate student learning and likely explain at least some of the difference in effectiveness across schools (Sanders and Rivers 1996; Nye, Konstantopoulos, and Hedges 2004; Rivkin, Hanushek, and Kain 2005; Rockoff 2004; Aaronson, Barrow, and Sander 2007; Kane, Rockoff, and Staiger 2008). Aaronson, Barrow, and Sander (2007) find that a 1 standard deviation improvement in math teacher quality, as measured by the test score gains of their students, raises students' math scores by the equivalent of 0.13 grade equivalents per semester. Kane, Rockoff, and Staiger (2008) find that the difference in effectiveness between the top and bottom quartiles of elementary schoolteachers leads to a 0.33 standard deviation difference in student test score gains in a school year. For middle schoolteachers the difference is about 0.20 standard deviations (Kane, Rockoff, and Staiger 2008).

Teachers are clearly one of schools' most important resources. Teachers are not, however, randomly assigned to schools or students. Schools vary considerably in the types of teachers they employ. Some of these differences are largely outside a school's control and are due to teachers' preferences for certain types of students or for schools located in certain geographic areas. Teacher preferences make it easier for some types of schools to attract candidates for open positions (Boyd et al. 2011) and easier for some types of schools to retain their effective teachers because they are more appealing places to work.

Though the quality of a school's teaching force is partially driven by teachers' preferences for certain types of schools, it is also likely to be at least partly the result of school policies and practices of school leaders. School leaders can control the quality of the teaching force at their school by hiring high-quality teachers, strategically retaining good teachers and removing poor teachers, and developing the teachers already at their school. Moreover, they can maximize the effectiveness of their available teachers by assigning them to classes for which they are best suited, which provides the most benefit to their school. Schools are likely to vary in their capacity to engage in each of these personnel practices. We know little about the extent to which these practices are defining features of effective schools.

A first step in effective personnel practices is an ability to identify strengths and weaknesses of teachers and teacher candidates. There is evidence that many school leaders can distinguish highly effective teachers both during the hiring process and from among the teachers currently employed at their school. While Rockoff et al. (2011) point out that information available about candidates at the time of hire may be limited, making it difficult for school administrators to recognize a good teacher when they are looking to hire one, Boyd et al. (2011) find that, on average, school leaders can recognize teacher effectiveness in the hiring process, especially when hiring teachers with prior teaching experience. Feng and Sass (2011) also find evidence consistent with these findings. In their study of Florida schools, they find that the most effective teachers tend to transfer to schools whose faculties are in the top quartile of teacher quality. However, whether such schools are better at selecting quality teachers or whether quality teachers are attracted to such schools remains unclear. There is even stronger evidence that school administrators can identify differences in the effectiveness of teachers currently working at their school. Jacob and Lefgren (2008) find that principals can identify the teachers at their school who are most and least effective at raising student achievement, though they have less ability to distinguish between teachers in the middle of the quality distribution. Jacob (2010) examines the weight that school administrators place on a variety of teacher characteristics when deciding which teachers to dismiss. He finds that principals consider teacher absences, value added to student achievement, and several demographic characteristics when making dismissal decisions.

Of course, even if school administrators are able to identify their least effective teachers, dismissing weak teachers is not always possible, particularly once teachers obtain tenure. Very few teachers are dismissed from schools, though dismissal rates are higher for less experienced teachers and may have risen slightly recently. Yet dismissal is not the only, or even the primary, way schools can facilitate the turnover of less effective teachers. Counseling out, less than prime class assignments, and the manipulation of other working conditions can all encourage teachers to leave particular schools, either by prompting them to transfer to other schools or to leave teaching all together (Balu, Béteille, and Loeb 2010). While these processes are acknowledged in the research literature, no study that we know of has documented systematic differences in the differential turnover of high- and low-quality teachers across schools of varying quality, which is a key component of our analyses. Several studies have found that high value-added teachers have lower turnover rates than low value-added teachers (Hanushek et al. 2005; Goldhaber, Gross, and Player 2007; West and Chingos 2009; Feng and Sass 2011). West and Chingos (2009) examine the relationship between teacher value added and turnover in high-poverty and high-minority schools. They find that although turnover rates are higher in schools with more poor or minority students, the relative difference in turnover rates between high and low value-added teachers in these schools is similar to the difference in other types of schools. Our study builds on this analysis by examining whether the relationship between teacher value added and turnover is different in more versus less effective schools.

Another way that schools can control the average quality of their teachers is by providing professional development or other avenues to develop the instructional skills of their teaching staff. Prior research suggests that teachers can improve substantially as they acquire more experience, particularly in their first few years of teaching (Rockoff 2004). Developing teachers' skills through professional development may be both the most viable and the most effective option for schools looking to improve the quality of their teaching force. Teacher development is likely to be an important part of teacher quality in all schools but may be particularly important in schools serving many low-achieving, poor, and minority students. These schools often face more difficulty attracting and retaining effective teachers (Ferguson 1998; Krei 1998; Lankford, Loeb, and Wyckoff 2002).

The process by which teachers are assigned to students is another component of personnel practices that may distinguish more effective from less effective schools. There is evidence from prior research that within schools, teachers with certain characteristics are systematically sorted to lower-achieving and more disadvantaged students than their colleagues (Clotfelter, Ladd, and Vigdor 2006; Rothstein 2009; Feng 2010). This type of allocation of teachers to students does not always seem to be done with students' best interests in mind (it is often based on seniority) and is likely to have negative implications for within-school achievement gaps and teacher retention (Feng 2010; Kalogrides, Loeb, and Béteille 2011). The processes by which teachers are allocated to students within schools may vary considerably across schools and in particular may happen more equitably in more effective schools.

In this article we examine whether there are differences in teacher hiring, assignment, development, and retention in more effective schools compared with less effective schools. We do not attempt to distinguish the part of recruitment and retention that is driven by school personnel practices from that driven by teacher preferences. Instead we measure the extent to which highly effective schools attract, assign, develop, and retain teachers differently than less effective schools. Our anlysis assumes that personnel decisions are somewhat decentralized and are made at the school rather than the district level. Prior research has found that M-DCPS has a decentralized management style (Wohlstetter and Buffett 1992). Our own survey data support this claim. We administered a survey to principals in Miami-Dade in the spring of 2011 (with a 75 percent response rate). We asked principals what level of discretion they had over hiring teachers at their school during the current school year. Seventy-six percent of principals said they had complete or partial discretion during the hiring process. Twenty-six percent of these principals said they had total discretion and could make hiring decisions without any input from the district. Only 11 percent of principals indicated they had no discretion in the hiring process. Therefore personnel decisions made at the school level are potentially important components of school effectiveness.

Understanding the importance of personnel practices for school effectiveness can have important policy implications. If more effective schools tend to recruit more effective teachers but not retain them, we can conclude that in the current system recruitment is a more salient factor in determining school effectiveness. If they retain their good teachers but do not develop them, we can again conclude that retention is more of a driving force in effective schooling. If they develop their teachers but do not differentially assign, we would conclude that unequal assignment of students to new teachers is not a reflection of less effective schooling. In fact, we find that more effective schools are better able to hire high-quality teachers, allocate their teachers to students more equitably, develop the teachers already at their school, and differentially retain high-quality teachers, though they do not differentially lose less effective teachers. In what follows, we describe the data and methods, present the results, and conclude with a discussion of the implications of the analyses.

3. DATA

To examine the role of personnel practices in school effectiveness, we use data from administrative files on all staff and students in the Miami-Dade County Public Schools (M-DCPS) district from the 2003–4 through the 2009–10 school years. M-DCPS is the largest school district in Florida and the fourth largest in the country, trailing only New York City, Los Angeles Unified, and the City of Chicago School District. In 2008 M-DCPS enrolled almost 352,000 students, more than 200,000 of whom were Hispanic. With more than 350 schools observed over a seven-year time frame, the data provide substantial variation for examining differences in school and teacher effectiveness.

We use measures of teacher and school effectiveness based on the math and reading achievement gains of students at a school or in a teacher's classroom. The test score data include math and reading scores from the Florida Comprehensive Assessment Test (FCAT). The FCAT is given in math and reading to students in grades 3–10. It is also given in writing and science to a subset of grades, though we use only math and reading tests for this article. The FCAT includes criterion-referenced tests measuring selected benchmarks from the Sunshine State Standards. We standardize students' test scores to have a mean of zero and a standard deviation of 1 within each grade and school year.

We combine the test score data with demographic information including student race, gender, free/reduced price lunch eligibility, and whether students are limited English proficient. We also link students to their teachers via a database that lists the course title, classroom identifier, and teacher of every course in which a student was enrolled in each year (including elementary school students who simply have the same teacher and classroom listed for each subject). We use the classroom identifier to generate classroom measures such as percentage of minority students, percentage of students receiving free or reduced price lunches, and average student achievement in the prior school year. We obtain M-DCPS staff information from a database that includes demographic measures, prior experience in the district, highest degree earned, current position, and current school for all district staff.

Table 1 lists the means and standard deviations of all variables used in our analyses. There are 351,888 unique tested students included in our estimation of value added, each of whom is included for an average of three years. Nearly 90 percent of students in the district are black or Hispanic, and more than 60 percent qualify for free or reduced price lunches. We were able to compute value-added estimates for about ten thousand teachers who taught students who were tested in math and reading. These teachers average approximately eight years of experience in the district, they are predominantly female (79 percent), and their racial composition is similar to that of students in that the majority are Hispanic.

4. METHODS

Estimating Value Added

The goal of value-added models is to statistically isolate the contribution of schools or teachers to student outcomes from all other factors that may influence outcomes (Meyer 1997; Rubin, Stuart, and Zanutto 2004). Isolating causal effects is important given that differences in student and family characteristics account for more of the variation in student outcomes than school-related factors (Coleman 1990; Downey, von Hippel, and Broh 2004) and that

Table 1. Descriptive Statistics

	Mean	SD
Student Characteristics		
Average standardized test score gain in math	0.01	0.65
Average standardized test score gain in reading	0.02	0.67
Standardized math score	−0.01	1.00
Standardized reading score	−0.10	1.00
Black	0.27	
Hispanic	0.61	
Female	0.50	
Limited English proficient	0.09	
Retained in year prior	0.07	
Eligible for subsidized lunch	0.61	
Total student observations (with test scores)	880,946	
Unique students (with test scores)	351,888	
Average number of observations per student	3	
Teacher Characteristics*		
Years in district	8.10	6.95
Black	0.28	
Hispanic	0.44	
Female	0.79	
Age	41.95	11.30
Master's degree or higher	0.36	
Number of teacher observations	29,251	
Number of teachers	10,326	
School Characteristics		
% eligible for subsidized lunch	0.65	0.25
% minority (black or Hispanic)	0.88	0.32
% scoring in lowest FCAT proficiency category in math	0.23	0.17
% scoring in lowest FCAT proficiency category in reading	0.28	0.18
Student enrollment	931	785
Elementary school	0.51	
Middle school	0.24	
High school	0.17	
Number of schools	441	

*Includes only teachers for whom we were able to compute value-added estimates.

students are not randomly assigned to teachers or schools (Lankford, Loeb, and Wyckoff 2002; Rothstein 2009).

A student's achievement level in any given year is a cumulative function of current and prior school, family, and neighborhood experiences. While researchers seldom have access to complete information on all factors that would predict a student's current achievement level (Rivkin, Hanushek, and Kain 2005), much of the confounding influence of unobserved student academic and family characteristics can be eliminated by focusing on *gains* in student achievement over specific time periods, usually one school year. The inclusion of prior achievement as a way of controlling for prior student or family experiences reduces the potential for unobserved factors to introduce bias in the estimation of teacher or school effectiveness. Yet there still may be unobservable differences between students that influence the amount they learn each year in addition to their score at the beginning of the year. Factors such as innate ability, motivation, familial support for education, or parental education could all have an impact on student learning gains. We can control for some of these differences by including student-level covariates in the model; however, the information available in administrative data sets such as ours is limited. One way of controlling for all observed and unobserved student characteristics that may be associated with achievement gains is to include a student fixed effect in the value-added estimation. Such a specification is appealing because it allows for the examination of differences in learning for the same student in years they are in a class with a different teacher or in years they are in different schools.

Equation 1 describes our school value-added model, which predicts the achievement gain between year $t-1$ and year t for student i with teacher j in school s as a function of time-varying student characteristics (X_{ijsts}), classroom characteristics (C_{jt}), time-varying school characteristics (S_{st}), student fixed effects (π_i), and a school by year fixed effect (δ_{st}):

$$A_{ijst} - A_{ijs(t-1)} = \beta X_{ijst} + \eta C_{jt} + \gamma S_{st} + \pi_i + \delta_{st} + \varepsilon_{ijst}. \tag{1}$$

The parameter δ reflects the contribution of a given school to growth in student achievement after controlling for all observed time-varying student characteristics, observed and unobserved time-invariant student characteristics, and characteristics of students' classrooms that may be associated with learning. It captures all the school-level factors that influence growth in student achievement. Note that these models account for all unobserved time-invariant attributes of students that may be associated with learning (via the student fixed effect) but not for differences across schools in unobservable time-varying student characteristics that are associated with learning. We use achievement gains as the outcomes in these models (rather than current year achievement as the outcome, with prior year achievement on the right-hand side) because they include student fixed effects; therefore these models show a school's effect on student achievement gains relative to students' average gains in years they attend other schools.

The model in equation 1 is identified from students who attend multiple schools during the observation period. Students may attend multiple schools for a variety of reasons, including residential relocation, expulsion, or transfers that result when students transition away from a school after completing the final offered grade. Since we have seven years of test data and students are tested in a wide range of grades (3–10), we observe over half of the tested students (52 percent) in two or more schools. However, given concerns that this group of students may not be representative of the full population of tested students, we compare the estimates derived from equation 1 with those derived from a similar model that excludes the student fixed effect and uses students' current year test score as the outcome, with a control for their prior year test score on the right-hand side.[1] Our school fixed effects estimates from these two specifications correlate fairly highly at .81 in math and .52 in reading.[2] In what follows we present estimates from models that use the measure of school value added that is estimated with the student fixed effect. However, in results not shown we also estimate all our models using the measure of school value added that is estimated without a student fixed effect. The results are substantively similar.

We estimate teacher value added using a model similar to that described by equation 1. We replace the school by year fixed effect with a teacher by year fixed effect. In the teacher value-added equation the parameter δ reflects the contribution of a given teacher to growth in student achievement each year, conditional on the characteristics described above. It shows whether the achievement gain for given students is higher or lower the year they have a particular teacher relative to their average gains from years they are in classes with other teachers. In addition to the specification of teacher value added with a student fixed effect and gain scores on the left-hand side of the equation, we also generate measures of teacher value added from two alternative specifications: (1) a model that includes a school fixed effect (without a student fixed effect), achievement in the current year as the outcome, achievement in the prior year on the right-hand side, and all other parameters as discussed above for equation 1; and (2) a model that excludes student and school fixed effects, includes achievement in the current year as the outcome, achievement in the prior year on the right-hand side, and all other parameters as discussed above for equation 1. We show the correlations among estimates from the alternative school and teacher value-added specifications in table 2.

1. The student fixed-effects models identify school effectiveness by whether a given student has greater gains in that school (controlling for time-varying student characteristics, classroom characteristics, and school characteristics) than that *same* student has when he or she attends a different school. The models without student fixed effects identify school effectiveness by whether a given student has greater gains in that school (controlling for student characteristics, classroom characteristics, and school characteristics) than an *observably similar* student in a different school.
2. There is no relationship between either measure of school value added and school average test scores. In math, for example, the correlation of school average math score with school value added estimated without student fixed effects is −.03 and with school value added estimated with student fixed effects is .05. These correlations are not statistically significant. The school value-added measures, therefore, are not picking up differences in average achievement levels between schools.

Table 2. Correlations among Alternative School and Teacher Value-Added Measures

	Correlations							Description of Value-Added Model Specification			
	(1)	(2)	(3)	(4)	(5)	(6)	Outcome	Prior Score on Right-Hand Side	School Fixed Effects	Student Fixed Effects	Other Controls
School Value Added											
(1) SVA1 math	1.00						Current score	Yes	No	No	Yes
(2) SVA2 math	0.81	1.00					Gain	No	No	Yes	Yes
(3) SVA1 reading	0.70	0.56	1.00				Current score	Yes	No	No	Yes
(4) SVA2 reading	0.38	0.64	0.52	1.00			Gain	No	No	Yes	Yes
Teacher Value Added											
(1) TVA1 math	1.00						Current score	Yes	No	No	Yes
(2) TVA2 math	0.94	1.00					Current score	Yes	Yes	No	Yes
(3) TVA3 math	0.71	0.64	1.00				Gain	No	No	Yes	Yes
(4) TVA1 reading	0.58	0.58	0.28	1.00			Current score	Yes	No	No	Yes
(5) TVA2 reading	0.54	0.58	0.22	0.91	1.00		Current score	Yes	Yes	No	Yes
(6) TVA3 reading	0.21	0.14	0.56	0.29	0.23	1.00	Gain	No	No	Yes	Yes

Notes: All value-added specifications include controls for student race/ethnicity, gender, whether students qualify for free lunches, whether they are currently classified as limited English proficient, whether they are repeating the grade in which they are currently enrolled, and number of days they missed school in a year due to absence or suspension. The models also include averages of these student-level variables at the school and classroom levels. In some models, time-invariant student-level measures (i.e., race/ethnicity, gender) are absorbed by the student fixed effects.

The three teacher value-added measures correlate fairly highly in math (between .64 and .94). The correlations are a bit lower for reading value added, especially for the models with student fixed effects. In the analysis presented below, we compare the results using all three measures of teacher value added.

The test scores used to generate the value-added estimates are the scaled scores from the FCAT, standardized to have a mean of zero and a standard deviation of 1 for each grade in each year. Subscripts for subjects are omitted for simplicity, but we estimate equation 1 separately for student achievement gains in math and reading. Gains in math and reading are attributed to teachers of self-contained elementary school classrooms for students in grades 5 and below. For older students (who have multiple teachers), gains in math and reading are attributed to math and English teachers. These teachers are identified from student course records, which list the course title and instructor for each of a student's courses in each year.

Since we use a lagged test score to construct our dependent variables (or as a control variable on the right-hand side in some specifications), the youngest tested grade (grade 3) and the first year of data we have (2003) are omitted from the analyses, though their information is used to compute a learning gain in grade 4 and in 2004. The time-varying student characteristics used in our analyses are whether students qualify for free or reduced price lunch, whether they are currently classified as limited English proficient, whether they are repeating the grade in which they are currently enrolled, and the number of days they missed school in a given year due to absence or suspension. Student race and gender are absorbed by the student fixed effect but are included in models that exclude the student fixed effect. The class- and school-level controls used in the models include all the student-level variables aggregated to the classroom and school levels.

After estimating equation 1 we save the school by year and teacher by year fixed effects and their corresponding standard errors. The estimated coefficients for these fixed effects include measurement error as well as real differences in achievement gains associated with teachers or schools. We therefore shrink the estimates using the empirical Bayes method to bring imprecise estimates closer to the mean (see the appendix). There is greater imprecision in our estimates of teacher value added than school value added, since teachers' class sizes are smaller than the total school enrollment in a given year. The number of students per teacher varies meaningfully. Teachers who teach small or few classes tend to have more imprecise estimates, since their estimates are based on fewer students. In addition to shrinking the estimates, we limit the sample to teachers who have at least ten students in a given year. Shrinking the school fixed effects tends not to change the estimates very much, given large samples in each school, but it does change the teacher fixed effects measures somewhat. The correlation between our original school by year fixed effect estimate and the shrunken estimate is about .99 for both math and reading. The correlation between our original teacher by year estimate and the shrunken estimate is .84 for math and .81 for reading for the teacher value-added estimates that include a student fixed effect. After shrinking the value-added estimates, we standardize them to have a mean of zero and a standard deviation of 1 in each year to facilitate interpretation.[3]

Teacher and school value added as measured by student achievement gains on state tests are clearly not perfect measures of effectiveness. While measuring effectiveness by how much students learn makes sense if we care about student learning, current test scores are a limited measure of students' learning outcomes that we care about. This is especially true at the secondary school level, where outcomes such as graduation rates and college preparedness may also be important measures of school effectiveness.[4] There also may be bias in attributing student test score gains to teachers even though our measures adjust for a rich set of student and classroom characteristics. On the positive side, recent research has demonstrated that higher value-added teachers, as measured in ways similar to those employed here, tend to exhibit stronger classroom practices as measured by observational protocol such as the Classroom Assessment Scoring System (La Paro, Pianta, and Stuhlman 2004) and Protocol for Language Arts Teaching Observation (Grossman et al. 2010). Nonetheless there is clearly measurement error in our estimates of teacher effectiveness, and there may be bias, as some teachers teach a higher proportion of students with negative shocks to their learning in that year, and some teachers likely teach relatively better in areas not covered as well by the standardized tests.

Teacher Recruitment, Assignment, Development, and Retention

We ask four questions in this study. First, to what extent do more effective schools hire more effective teachers when vacancies arise? Second, do more

3. School value added fluctuates somewhat over time, but there are fairly high correlations within schools between current and prior year value added. In versions of school value added that are estimated without student fixed effects, the correlation between current year value added and prior year value added is .50 in both math and reading. In versions of school value added that are estimated with student fixed effects, the correlation between current year value added and prior year value added is .73 in reading and .82 in math. Variation in school value added over time could be due to a variety of factors, such as changes to the leadership or changes to faculty composition. However, we do not examine what contributes to these changes over time.
4. We do not have data on these types of non–test score outcomes so cannot evaluate school effectiveness based on these measures. However, to the extent that students who learn more in high school are better prepared for college and are more likely to graduate from high school, evaluating secondary schools based on student learning gains remains a relevant endeavor.

effective schools handle teacher class assignments more equitably than less effective schools? Third, do teachers improve in effectiveness more rapidly when they work in more effective schools? And finally, to what extent do more effective schools retain more effective teachers and remove less effective teachers?

Recruitment and Hiring

Effective schools may hire more effective teachers when vacancies arise. In order to examine this issue, we ask whether more effective teachers transfer to more effective schools. We are unable to examine whether more effective schools hire higher-quality new teachers because our measure of effectiveness cannot be computed for teachers who have not taught students in a tested subject for at least one year. Therefore this analysis is restricted to teachers who transfer in the following year and for whom we have value-added measures in the year before they switch schools.[5] In particular, we ask whether the teachers who transfer to more effective schools had higher value added (in the year before they transferred) than teachers who transfer to less effective schools.

The following equations describe the models:

$$TE_{jgxst} = \alpha + \beta_1(SE_{xt}) + \pi_t + \pi_g + \varepsilon_{jgxst} \tag{2a}$$

$$TE_{jgxst} = \alpha + \beta_1(SE_{xt}) + T_{jxst}\beta_2 + \pi_t + \pi_g + \varepsilon_{jgxst} \tag{2b}$$

$$TE_{jgxst} = \alpha + \beta_1(SE_{xt}) + T_{jxst}\beta_2 + S_{st}\beta_3 + \pi_t + \pi_g + \varepsilon_{jgxst} \tag{2c}$$

$$TE_{jgxst} = \alpha + \beta_1(SE_{xt}) + T_{jxst}\beta_2 + S_{st}\beta_3 + S_{xt}\beta_4 + \pi_t + \pi_g + \varepsilon_{jgxst} \tag{2d}$$

In the base model, equation 2a, the effectiveness (TE) in year t of teacher j who worked in school s in time t and transferred to school x in time $t+1$ is a function of the effectiveness of the school he or she transferred to (SE) measured in year t, as well as year (π_t) and grade (π_g) indicators. For example, suppose we observe a teacher in school s in 2006. In 2007 the teacher is observed in school x. In this case the teacher's value added in 2006 is the outcome and the value added in 2006 of school x is the predictor. The coefficient on SE measures whether more effective schools differentially attract more effective teachers. We cluster the standard errors by the level of the hiring school, since school value added is measured at that level. Since teacher value added is the

5. Teachers who transfer are systematically different in many ways from those who never transfer during our sample period. They tend to have more experience (8.6 vs. 7.5 years), are less likely to be Hispanic (39 percent vs. 45 percent), are a bit older (42 vs. 40 years), and are less likely to hold a master's degree (36 percent vs. 40 percent). Teachers who transfer also have lower value added in math and reading compared with teachers who stay in the same school.

outcome variable in these analyses, we use the raw (standardized) fixed effects for teachers in this analysis as opposed to the shrunk estimates. Using the empirical Bayes shrinkage to account for measurement error in the teacher fixed effects is necessary only for unbiased estimates when these measures are used on the right-hand side of our equations, though the results are similar when using either method. We estimate these models pooled by grade level and separately by grade level.

While equation 2a answers the research question, we are interested in exploring a number of explanations for the observed relationship, β_1. Equations 2b–2d describe this exploration. First we introduce other teacher characteristics (T), including experience, highest degree earned, age, race, and gender. This model (2b) asks whether the relationship between teacher and school effectiveness is explained by other observable teacher characteristics on which these more effective schools might base hiring. Next we add in additional controls for the characteristics of the hiring school (S_x). Model 2c asks whether the relationship between teacher and school effectiveness is driven by other characteristics of the hiring school that might attract teachers, such as size or student characteristics, instead of effectiveness. More and less effective schools may differ in the number of vacancies they have each year. This could induce a correlation between teacher and school effectiveness even if both types of schools select the most competent applicants from the same population, since less effective schools would have to go further down the effectiveness distribution to fill all openings. To adjust for this possibility, model 2c includes a control variable for the number of first-year transfer teachers working at the school in a given year. This is the number of teachers at a school who taught at a different school in the district in the prior year.

The final model (2d) adds in controls for the school in which the teacher taught the year before his or her transfer (S_s). This inclusion helps uncover whether more effective schools are hiring teachers from specific kinds of schools, particularly those that produce high value-added transferring teachers. It may be, for example, that the hiring school does not have a good estimate of the value added of each teacher but judges them based on the school from which they came, and in that way is able to identify more effective teachers.

While models 2b–2c provide suggestive evidence on some of the mechanisms behind the univariate relationship between school value added and the value added of transfers, we do not have data on applications and offers, thus we cannot discern whether more effective schools hire more effective transferring teachers because more effective teachers apply to more effective schools or because more effective schools are better able to identify the most effective teachers out of their pool of applications.

Novice Teacher Assignments

Our second research question is whether novice teachers receive different types of class assignments when they work in more effective schools. The following equation describes the model:

$$Y_{itsg} = \beta_0 + \beta_1(Novice)_{itsg} + \beta_2(SE_{st}XNovice_{itsg}) + T_{itsg}\beta_3 + \pi_{stg} + \varepsilon_{itsg}. \quad (3)$$

We predict a class characteristic for teacher *i* in year *t* in school *s* and in grade *g*, Y_{itsg}, as a function of whether the teacher is a first- or second-year teacher (which is our definition of a novice teacher); teacher background measures (race, gender, age, and highest degree earned); T_{itsg}, an interaction between school effectiveness and the novice teacher indicator; and a school by year by grade fixed effect, π_{stg}.

The estimate β_1 shows the difference in the attributes of the students assigned to novice versus more experienced teachers in schools that are of average effectiveness (i.e., where school effectiveness is zero). The estimate β_2 shows whether the magnitude of this relationship varies by school effectiveness. Our inclusion of the school by year by grade fixed effect means that our estimates reflect differences in class assignments for teachers of varying experience or demographic characteristics teaching the same grade and in the same school in the same year. The main effect on school value added is absorbed by the school by year by grade fixed effect. Our outcomes include the average prior achievement of teachers' current students in math and reading and the proportion of teachers' current students scoring in the highest and lowest FCAT proficiency levels in the prior year in math and reading. We conduct these analyses separately by school level, since there may be more opportunities for teacher sorting at the middle/high school grades than at the elementary school grades due to curricular differentiation. We also exclude special education teachers from these models, since they have lower scoring students in their classes and the assignment process likely works differently for these types of teachers.

Teacher Development

Our third set of models tests whether the value added of teachers changes more across years when they are in an effective school. To examine this we test whether teachers' value added changes more between years when they are employed at a school that was more effective in a prior period. We regress teacher value added in the current year on teacher value added in the prior year and school value added measured two years prior. We use a two-year lag of the school's value added so that school and teacher effectiveness are not estimated from the same test score data. For example, suppose the outcome (teacher value added) is measured in 2008: 2007 and 2008 test data are used to compute teacher value added in 2008; 2006 and 2007 data are used to compute the prior year's (2007) teacher value added; and 2005 and 2006 data are used to compute school value added two years ago (2006). Although school value added fluctuates over time due either to real changes in school performance or to measurement error, the correlation between current and prior year school value added is between .65 and .80, as is the correlation between current year and twice lagged school value added. Since we control for the lag of teacher value added, the coefficients on the other variables in the model indicate *change* in their value added as a function of a covariate. All specifications control for school year, grade taught, and teacher experience, which are entered as dummy variables. We control for grade taught, since students may exhibit lower learning gains in some grades than in others, and control for teacher experience, since prior studies suggest the rate at which teachers improve tends to flatten after their first few years of teaching.

The model is shown by the following equation:

$$\begin{aligned} TE_{jgmt} &= \alpha + \beta_1\left(TE_{jgm(t-1)}\right) + \beta_2\left(SE_{m(t-2)}\right) \\ &\quad + (T\exp_{jgmt})\beta_3 + \pi_t + \pi_g + \varepsilon_{jgmt} \end{aligned} \tag{4}$$

where TE_{jgmt} is teacher effectiveness in subject m in the current year, $TE_{jgm(t-1)}$ is teacher effectiveness in the prior year, $SE_{m(t-2)}$ is school effectiveness two years ago, *Texp* are dummy variables for teacher experience, and π_t and π_g are year and grade fixed effects, respectively. We estimate this model for all teachers regardless of whether they had changed schools since the year prior but also compare these estimates with those from a model restricted to teachers who remained in the same school and find similar results.

One worry with the model described in equation 4 is that measurement error in prior year teacher effectiveness biases the estimation. Shrinking the estimates accounts for sampling error, but there could be other types of error in this particular analysis that we may need to worry about—error that comes from factors that produce variation in teacher effectiveness from year to year (such as a barking dog when students are taking the test). In particular, consider two teachers with equal value added in a given year. The teacher in the better school may normally be a better teacher and thus have a tendency to revert back to her higher average, while a teacher in a less effective school may normally be a worse teacher and similarly reverts back to her lower average value added. This would be a classic case of mean reversion and would upwardly bias our estimate of the relationship between school effectiveness and growth in teacher effectiveness. To adjust for this error, we instrument for prior year value added in a given subject using prior year value added in the other subject. That is, in analyses that examine changes to math value added, we instrument for prior math value added using prior reading value added, and vice versa. These analyses are necessarily restricted to elementary schoolteachers who have classes with students tested in both subjects. We present the instrumental variable (IV) estimates along with the ordinary least squares (OLS) estimates in the results section; both methods produce similar results.

Retention

Fourth and finally, we examine the association between teacher turnover, teacher effectiveness, and school effectiveness using logit models to predict whether a teacher leaves his or her school at the end of a year as a function of school value added, teacher value added, and the interaction between the two. Here we are asking whether more effective teachers are differentially more likely to leave (or stay at) more effective schools. Equation 5 describes the model:

$$\Pr(Y_{ist} = 1) = \frac{e^f}{1 + e^f}$$

where

$$f = T_{jst}\beta_1 + \beta_2 TE_{jst} + S_{st}\beta_3 + \beta_4 SE_{st} + \beta_5(SE_{st} X TE_{jst}) + \pi_s + \varepsilon_{jst}. \tag{5}$$

The outcome Y is the probability that teacher j in school s in time t will not return to his school in time $t + 1$ and is estimated as a function of the teacher's own characteristics, not including effectiveness (T), his or her effectiveness (TE), the school's characteristics (S), the school's effectiveness (SE), and the interaction between the school's and the teacher's effectiveness. The model also includes school fixed effects, so comparisons of turnover rates are made among teachers who vary in effectiveness at the same school. The coefficient on the interaction in this model, β_5, tells us whether there are differential career paths for teachers of varying effectiveness as a function of the school's effectiveness. We cluster the standard errors in these models at the school level since the observations are not independent.

In addition to using continuous measures of school and teacher value added, we also estimate models that use quartiles of these measures. Prior research suggests that principals have difficulty distinguishing among teachers at their school who are in the middle of the quality distribution, but they are able to distinguish between those at the top and bottom in terms of effectiveness (Jacob and Lefgren 2008). If principals are to target their retention efforts on particular teachers, they must be able to distinguish among the best and worst teachers at their school. We therefore generate quartiles of teacher value added (within each school) and include dummy variables flagging teachers in the top and bottom quartiles. For this analysis we also use a measure that distinguishes schools in the top quartile of school value added (generated within each year and school level) instead of using the continuous measure.

Since teacher and school value added are each measured separately in each year, these estimates tell us whether schools that were more effective in one year are better able to keep their more effective teachers and remove their less effective teachers the following year. Our use of measures of value added that vary by year is important for our estimation strategy. Though pooling value-added measures across years may be preferable given small samples for some teachers and measurement error in tests (McCaffrey et al. 2009), in our case this makes the causal ordering of these measures ambiguous. In the teacher turnover analyses, for example, we want to test whether more effective schools are able to keep good teachers and remove ineffective ones. We also want to be able to rule out an alternative explanation (of a reversal in causal ordering) that schools look as though they have higher value added only because they happen to have particularly good teachers. For example, if we estimated school value added in the year after less effective teachers left and more effective teachers stayed, the school would look more effective regardless of its practices in the prior years that led to this differential turnover. While the year-by-year measures of school and teacher effectiveness are less precise than measures averaged over all years, the value added based on prior years allows us to examine how school effectiveness in a given period influences teacher turnover behavior in a subsequent period and helps us avoid the problems described above.[6]

5. RESULTS

Recruitment and Hiring

More effective schools may hire higher value-added teachers when vacancies arise. This differential hiring may be driven by proactive recruitment efforts by such schools, a better ability to distinguish among job candidates, or teachers'

6. There is some concern in the value-added literature about issues with nonpersistent teacher effects. McCaffrey et al. (2009), for example, find that between 30 and 60 percent of the variation in measured teacher effectiveness is due to "noise" in student test scores rather than to real differences between teachers. The proposed solution is to either average teacher effects over multiple years or take teacher by year fixed effects and estimate the true signal variance by the covariance of these effects across years. However, this method will not work in our case. For the analyses described below we require measures of value added for teachers and schools that are estimated separately in each year to avoid problems such as circularity and reverse causation.

preferences for more effective schools. While we cannot separate the possible mechanisms, table 3 shows some evidence of differential hiring among elementary schoolteachers. In these models we take all teachers who transfer and regress the value added of the teacher who transfers (measured in the year prior to her transfer) on the effectiveness of the school to which she transfers (measured in the year prior to the teacher's transfer). We estimate each of these models for the version of teacher value added that includes and excludes student fixed effects. We do not show estimates using the version of teacher value added that includes school fixed effects because we are not interested in comparing teachers in the same school for these analyses.

The coefficients are positive across all specifications for elementary schoolteachers, suggesting that higher value-added teachers tend to transfer to more effective schools. The estimates, however, lack precision given the limited number of transferring teachers we observe for whom we are also able to estimate value added. The magnitudes of the coefficients change little across models with the introduction of additional teacher- and school-level control variables. This suggests that teacher effectiveness is not associated with other teacher characteristics that more effective schools look for when hiring (e.g., teacher experience) and that observable school characteristics that might influence teachers' transfer decisions bear little association with school value added.

Taken together, these findings provide some evidence that more effective elementary schoolteachers tend to move to more effective schools, though we cannot discern whether this results from differential personnel practices or from teachers' preferences for more effective schools. There is no evidence that more effective middle and high schools hire higher value-added transferring teachers. Value added may be harder to observe among teachers at this level, since only a subset of teachers provide instruction in tested subjects and the learning gains of older students are likely to be smaller.

Novice Teacher Assignments

Table 4 describes variation separately by school level in novice teachers' class assignments by school effectiveness. We show the results using both current school value added to predict class assignments and prior year school value added in case current effectiveness is influenced by the distribution of teachers to students. The results are largely the same in direction and magnitude.

The table shows consistent evidence that novice teachers are assigned lower achieving students than their colleagues across all types of schools. However, the magnitudes of these relationships are weaker in more effective schools—especially among elementary schoolteachers. For example, the main effect on

Table 3. Regression Predicting the Value Added of Teachers Who Transfer to More Effective Schools (Coefficients/Standard Errors)

	Elementary School Teachers				Middle/High School Teachers			
	1	2	3	4	1	2	3	4
Teacher Value Added Estimated with Student, School, and Class Controls								
Teacher Value Added in Math								
School value added	0.025	0.043	0.055	0.067	0.064	0.072	0.075	0.072
	(0.055)	(0.056)	(0.058)	(0.057)	(0.050)	(0.050)	(0.053)	(0.052)
N	465	465	465	465	499	499	499	499
Teacher Value Added in Reading								
School value added	0.071	0.080+	0.086+	0.068	0.006	0.024	0.032	0.052
	(0.046)	(0.047)	(0.048)	(0.047)	(0.054)	(0.052)	(0.055)	(0.054)
N	492	492	492	492	462	462	462	462
Teacher Value Added Estimated with Student Fixed Effects and Student, School, and Class Controls								
Teacher Value Added in Math								
School value added	0.053	0.059	0.077	0.089	0.020	0.027	0.027	0.028
	(0.053)	(0.054)	(0.055)	(0.055)	(0.055)	(0.056)	(0.059)	(0.059)
N	465	465	465	465	496	496	496	496
Teacher Value Added in Reading								
School value added	0.112**	0.110*	0.120**	0.121**	−0.003	−0.001	0.002	−0.001
	(0.043)	(0.043)	(0.044)	(0.044)	(0.049)	(0.049)	(0.052)	(0.052)
N	492	492	492	492	462	462	462	462
Teacher controls	–	X	X	X	–	X	X	X
New school controls	–	–	X	X	–	–	X	X
Current school controls	–	–	–	X	–	–	–	X
Clustered standard errors (by hiring school)	X	X	X	X	X	X	X	X

Notes: The models are restricted to teachers who transfer to a new school in the following year. Teacher value added is measured the year before they transfer, while school value added refers to the value added of the school to which they transfer (measured the year before the teacher arrives). School value added is estimated via a model that predicts the gain in student achievement as a function of time-varying student-, school-, and class-level control variables, student fixed effects, year and grade fixed effects, and a school by year fixed effect. In the top panel, teacher value added is estimated by predicting student achievement in the current year as a function of achievement in the prior year; student-, school-, and class-level controls; year and grade fixed effects; and a teacher by year fixed effect. In the bottom panel, teacher value added is estimated using the same model used to predict school value added. The teacher-level control variables used in these models include teacher race, gender, highest degree earned, age, age squared, and years of experience in the district. The school-level control variables used in these models include percent of students receiving free lunch, percent minority students, log of total enrollment, and number of first-year transfer teachers employed by the school in a given year.

$^{+}p <= .10$; $^{*}p <= .05$; $^{**}p <= .01$

novice teachers in the first column under the first panel shows that novice teachers are assigned students whose average prior achievement in math is .05 standard deviations lower than the average prior achievement of their more experienced colleagues at their school (in schools at the mean of effectiveness). The interaction between novice teacher and school value added in this model is a positive .04, suggesting that the effect is only about a quarter as large in

Table 4. Variation in Novice Teacher Class Assignments by School Value Added in Math (Coefficients/SEs)

	Elementary School Teachers		Middle/High School Teachers	
	School Value Added Measured in Current Year	School Value Added Measured in Prior Year	School Value Added Measured in Current Year	School Value Added Measured in Prior Year
Prior Math Achievement of Teachers' Current Students				
Novice teacher	−0.050***	−0.044**	−0.075***	−0.076***
	(0.013)	(0.015)	(0.007)	(0.008)
Novice teacher*School value added	0.036**	0.037*	0.013+	0.015
	(0.013)	(0.015)	(0.008)	(0.009)
N	18,752	13,896	30,865	22,822
Prior Reading Achievement of Teachers' Current Students				
Novice teacher	−0.041**	−0.036*	−0.078***	−0.077***
	(0.014)	(0.017)	(0.008)	(0.009)
Novice teacher*School value added	0.039**	0.037*	0.016+	0.018+
	(0.014)	(0.017)	(0.009)	(0.010)
N	18,753	13,899	30,879	22,830
Percentage of Low-Achieving Students in Math				
Novice teacher	0.012**	0.007	0.024***	0.023***
	(0.005)	(0.005)	(0.003)	(0.003)
Novice teacher*School value added	−0.015**	−0.009	−0.002	−0.003
	(0.005)	(0.005)	(0.003)	(0.003)
N	18,823	13,952	30,874	22,829
Percentage of High-Achieving Students in Math				
Novice teacher	−0.013***	−0.013***	−0.013***	−0.014***
	(0.002)	(0.003)	(0.001)	(0.002)
Novice teacher*School value added	0.005*	0.007*	0.002	0.002
	(0.002)	(0.003)	(0.001)	(0.002)
N	18,823	13,952	30,874	22,829
Percentage of Low-Achieving Students in Reading				
Novice teacher	0.002	−0.000	0.029***	0.025***
	(0.006)	(0.007)	(0.003)	(0.004)
Novice teacher*School value added	−0.015**	−0.011	−0.006+	−0.010*
	(0.006)	(0.007)	(0.004)	(0.004)
N	18,821	13,954	30,893	22,842
Percentage of High-Achieving Students in Reading				
Novice teacher	−0.008***	−0.008***	−0.009***	−0.010***
	(0.002)	(0.002)	(0.001)	(0.001)
Novice teacher*School value added	0.004*	0.006**	0.002*	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
N	18,821	13,954	30,893	22,842
School by year by grade fixed effect	X	X	X	X
Teacher-level controls	X	X	X	X

Notes: School value added is estimated via a model that predicts the gain in student achievement as a function of time-varying student-, school-, and class-level control variables, student fixed effects, year and grade fixed effects, and a school by year fixed effect. Novice teachers are those in their first or second year working in the district.
$^{+}p <= .10$; $^{*}p <= .05$, $^{**}p <= .01$, $^{***}p <= .001$

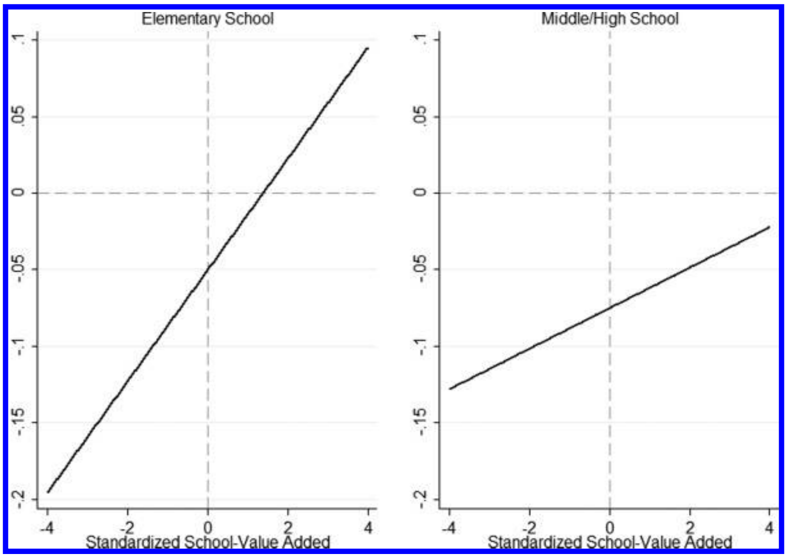

Figure 1. Within-School Novice-Nonnovice Difference in Average Prior Math Achievement of Students in Class, by School Value Added. Notes: The average prior year math achievement of students in teachers' classes each year is predicted as a function of an indicator flagging novice teachers, an interaction between novice teacher and school value added and a school by year by grade fixed effect. Teacher gender, race, age, and highest degree are held at their sample means. The estimates being graphed are the within-school gaps between novice and nonnovice teachers in the average prior year math achievement of students in their classes.

schools that are 1 standard deviation above the mean of school value added. For elementary schoolteachers, the results are similar for the average prior reading achievement of teachers' students as well as for the percentage of teachers' students who scored at the highest and lowest proficiency level on the FCAT in the prior year.[7] For middle/high schoolteachers, the coefficients on the interaction terms are smaller in size but are in the expected directions. The size of these differences is relatively large. The within-school grade-year standard deviation in average classroom prior math achievement is about .50 in both elementary school and middle/high school. Therefore the first column and row of table 4 shows that novice teachers' classrooms are one-tenth of a standard deviation lower achieving in math than the classrooms of their more experienced colleagues.

To more easily see these results, we plot the estimates in figure 1. The model on which the figure is based includes the average prior math achievement

7. One factor that could influence the extent to which schools assign novice teachers to lower-achieving students is the standard deviation of achievement within schools. We found only a very weak relationship between school value added and the standard deviation of math achievement. The correlations are −.04 in elementary schools and −.10 in high schools.

of teachers' current students as the outcome. The estimates that are graphed show the novice-nonnovice teacher gap in the prior average math achievement of their assigned students by school value added. In elementary schools 2 standard deviations below the mean of school value added, novice teachers are assigned students whose average prior math achievement is about .12 standard deviations lower than the average prior achievement of their colleagues' students. In elementary schools 2 standard deviations above the mean of school value added, novice teachers are assigned students whose average prior math achievement is similar to, if not slightly higher than, the average prior achievement of their colleagues' students. The trend is similar among middle/high schoolteachers, though the slope of the line is not as steep. These results provide clear and consistent evidence that more equitable assignments for novice teachers distinguish effective elementary schools from less effective elementary schools, though the assignment of lower achieving students to novice teachers happens to a similar extent in more and less effective middle/high schools.

Teacher Development

Next we investigate whether teachers improve their ability to raise student achievement more rapidly when working in effective schools. We restrict these analyses to teachers who have been employed in the district for five or fewer years. Prior research suggests that teachers' ability to raise student achievement increases considerably over the first few years in the teaching profession but remains relatively stable thereafter (Clotfelter, Ladd, and Vigdor 2006; Rivkin, Hanushek, and Kain 2005). The potential for school processes to influence teachers' effectiveness is therefore greater during the first few years of teaching. In table 5 we examine the relationship between the change in teacher value added between the current and prior year and the school's effectiveness two years ago. The reason we measure school value added two years ago is because of concern that if we used concurrent value added the effects might be circular, since the teacher's value added in the prior year is also in the model, and the teacher and school measures were estimated on the same data. We use measures of teacher value added that are estimated with and without student fixed effects. We exclude the version of teacher value added estimated using school fixed effects because in these analyses we are not interested in comparing teachers within the same school but rather teachers who teach in different schools (i.e., more and less effective schools). We present both OLS estimates (in the first four columns of table 5) and IV estimates (in the final four columns of table 5).

Both the OLS and IV estimates show a fairly consistent relationship between school effectiveness and teacher improvement in math value added. The

Table 5. Gains in Teacher Value Added (TVA) by School Value Added, Elementary School Teachers with Five or Fewer Years of Experience

	Ordinary Least Squares (OLS)				Instrumental Variable (IV)			
	Math		Reading		Math		Reading	
	1	2	1	2	1	2	1	2
TVA Estimated with Student, School, and Class Controls								
Teacher value added in prior year	0.538**	0.512**	0.482**	0.468**	0.669**	0.664**	0.638**	0.632**
	(0.019)	(0.020)	(0.021)	(0.022)	(0.034)	(0.035)	(0.038)	(0.038)
School value added two years ago	0.061*	0.061*	–0.002	–0.009	0.055*	0.055*	–0.006	–0.012
	(0.020)	(0.020)	(0.023)	(0.023)	(0.020)	(0.020)	(0.023)	(0.023)
TVA Estimated with Student Fixed Effects and Student, School, and Class Controls								
Teacher value added in prior year	0.427**	0.401**	0.359**	0.305**	0.466**	0.423**	0.431**	0.397**
	(0.024)	(0.024)	(0.026)	(0.027)	(0.064)	(0.065)	(0.067)	(0.068)
School value added two years ago	0.087*	0.101**	0.080*	0.085**	0.083*	0.098**	0.073*	0.075*
	(0.027)	(0.027)	(0.026)	(0.026)	(0.028)	(0.028)	(0.026)	(0.026)
N (observations)	1,759	1,759	1,842	1,842	1,759	1,759	1,842	1,842
Teacher-level controls	–	X	–	X	–	X	–	X

Notes: School value added is estimated via a model that predicts the gain in student achievement as a function of time-varying student-, school-, and class-level control variables, student fixed effects, year and grade fixed effects, and a school by year fixed effect. In the top panel, teacher value added is estimated by predicting student achievement in the current year as a function of achievement in the prior year; student-, school-, and class-level controls; year and grade fixed effects; and a teacher by year fixed effect. In the bottom panel, teacher value added is estimated using the same model used to predict school value added. The teacher-level control variables used in these models include teacher race, gender, highest degree earned, age, age squared, and years of experience in the district. The school-level control variables used in these models include percent of students receiving free lunch, percent minority students, log of total enrollment, and number of first-year transfer teachers employed by the school in a given year. In the IV models, we instrument for prior teacher value added in a given subject with their value added in the opposite subject. That is, we instrument for value added in math with value added in reading and for value added in reading with value added in math.

*$p <= .01$; **$p <= .001$

estimates are positive and significant for reading value added when we use the version of teacher value added that includes student fixed effects but are about zero and not significant in the version of teacher value added that excludes student fixed effects. When we look at the IV estimates for the version of teacher value added estimated with student fixed effects (bottom panel of table 4), we find that a 1 standard deviation increase in school value added (measured two years ago) is associated with a .08–.10 greater increase in teacher value added over a one-year period. The size of these estimates is fairly large—an increase in teacher value added of .10 is about the average improvement experienced by teachers from their first to second years.[8] Therefore working in a more effective school improves teachers' ability to raise student achievement by an amount similar to gaining an extra year of experience early in their careers. These results are consistent when we restrict the models to teachers who taught at the same school in the years in which we measure change in their value added.

Retention

Finally, we examine whether more effective schools are better able to retain their best teachers and remove their least effective teachers. In table 6 we show results from logistic regression models that predict whether a teacher leaves his school at the end of the year as a function of his own value added, the school's value added, or the interaction between the two. All models include controls for teacher and school characteristics and school fixed effects. We control for teacher and school characteristics to adjust for factors that might be associated with teacher turnover and teacher effectiveness. We include the school fixed effect so our comparisons are made only among teachers who vary in effectiveness within schools. Note that the main effects on school value added (not shown) are identified from within-school variation (over time) in value added but that interactions between school and teacher value added are identified from both within- and between-school variation in value added, since teacher value added varies within school years. Both school and teacher value added have been standardized to have a mean of zero and a standard deviation of 1 within each school year. We restrict these analyses to teachers who have been employed in the district for five or fewer years. Rates of transfer and attrition from the district are more than twice as large for less experienced teachers relative to older and more experienced teachers. The latter set of

8. The difference in effectiveness between first- and second-year teachers was estimated by predicting teacher value added as a function of indicators for teacher experience, year, and grade dummies and a teacher fixed effect (for elementary schoolteachers). The size of this estimate is similar in math and reading and for different ways of specifying the value-added equation.

Table 6. Logistic Regression of Teacher Turnover by Teacher and School Value Added (TVA/SVA), Teachers with Five or Fewer Years of Experience

	Odds Ratios/*t*-Statistics			Marginal Differences/Standard Errors		
	1	2	3	1	2	3
Math Value Added, Continuous Measures						
Teacher value added	0.811***	0.832***	0.786***	−0.027***	−0.026***	−0.027***
	(−6.508)	(−6.437)	(−6.657)	(0.004)	(0.004)	(0.004)
School*Teacher value added	0.925*	0.940*	0.934*	−0.009*	−0.009*	−0.007*
	(−2.378)	(−2.004)	(−2.077)	(0.004)	(0.004)	(0.004)
Math Value Added, Quartile Measures						
Teacher value added: Bottom quartile	1.342***	1.378***	1.267***	0.044***	0.045***	0.037***
	(4.220)	(4.558)	(3.385)	(0.009)	(0.009)	(0.010)
Teacher value added: Top quartile	1.004	1.043	0.952	−0.003	0.004	−0.008
	(0.052)	(0.505)	(−0.585)	(0.012)	(0.012)	(0.011)
School value added: Top quartile	1.177+	1.113	1.114	0.026+	0.023+	0.023
	(1.682)	(1.094)	(1.100)	(0.014)	(0.014)	(0.014)
TVA bottom quartile*SVA top quartile	0.907	0.979	1.053	0.003	0.006	0.015
	(−0.702)	(−0.151)	(0.349)	(0.021)	(0.020)	(0.022)
TVA top quartile*SVA top quartile	0.579***	0.659**	0.734*	−0.064**	−0.065**	−0.036*
	(−3.515)	(−2.705)	(−2.116)	(0.023)	(0.023)	(0.018)
Teacher and school controls	X	X	X	X	X	X
School fixed effect	X	X	X	X	X	X
N	10,333	10,333	10,325	10,333	10,333	10,325
Reading Value Added, Continuous Measures						
Teacher value added	0.914**	0.909**	0.934*	−0.012**	−0.012**	−0.008*
	(−3.226)	(−3.260)	(−2.063)	(0.004)	(0.004)	(0.004)
School*Teacher value added	0.981	0.970	0.982	−0.002	−0.003	−0.002
	(−0.687)	(−1.038)	(−0.623)	(0.004)	(0.004)	(0.004)

Table 6. Continued.

	Odds Ratios/*t*-Statistics			Marginal Differences/Standard Errors		
	1	**2**	**3**	**1**	**2**	**3**
Reading Value Added, Quartile Measures						
Teacher value added: Bottom quartile	1.008	1.056	0.996	0.007	0.009	−0.001
	(0.116)	(0.793)	(−0.053)	(0.009)	(0.009)	(0.009)
Teacher value added: Top quartile	0.839*	0.848*	0.922	−0.023*	−0.017	−0.015
	(−2.246)	(−2.129)	(−1.051)	(0.011)	(0.010)	(0.010)
School value added: Top quartile	1.093	1.114	1.084	0.016	0.021	0.016
	(0.927)	(1.124)	(0.832)	(0.014)	(0.014)	(0.014)
TVA bottom quartile*SVA top quartile	1.001	0.991	1.031	−0.008	−0.013	−0.022
	(0.004)	(−0.066)	(0.207)	(0.021)	(0.021)	(0.022)
TVA top quartile*SVA top quartile	0.812	0.756+	0.832	−0.028	−0.048*	−0.018
	(−1.390)	(−1.837)	(−1.290)	(0.022)	(0.022)	(0.021)
Teacher and school controls	X	X	X	X	X	X
School fixed effect	X	X	X	X	X	X
N	11,293	11,293	11,293	11,293	11,293	11,293
Overall probability of leaving	0.180	0.180	0.180	0.180	0.180	0.180

Notes: The outcome is whether the teacher leaves his or her current school at the end of the school year. Models 1, 2, and 3 differ in terms of the measure of teacher value added used. Model 1 uses a version of teacher value added estimated with student-, class-, and school-level controls and uses current test score as the outcome and prior year test score on the right-hand side. Model 2 is identical to model 1 except that it also includes a school fixed effect. Model 3 uses a version of teacher value added estimated with a student fixed effect and student-, class-, and school-level controls and uses the difference in achievement between the current and prior year as the outcome. The version of school value added used is analogous to the version of teacher value added used in model 3.

$^{+}p <= .10$; $^{*}p <= .05$; $^{**}p <= .01$; $^{***}p <= .001$

teachers is much less likely to leave their school or the district.[9] In addition to using continuous measures of value added, we also break these measures into quartiles and examine the retention of low (bottom quartile) and high (top quartile) teachers in the most effective schools (top quartile). As with the previous analyses, we show these results using three different measures of teacher value added. The first three columns of the table show odds ratios and *t*-statistics, while the last three columns show the marginal differences in probabilities and their corresponding standard errors.

The models that use the continuous measures of math value added suggest that teachers who are more effective at raising math achievement are less likely to leave their school, which is consistent with prior research (Hanushek et al. 2005; Goldhaber, Gross, and Player 2007; Boyd et al. 2008). For example, the main effect on teacher value added in the first column suggests that a 1 standard deviation increase in teacher math value added is associated with a 20 percent decline in the odds of leaving one's current school (in schools that are of average effectiveness). This corresponds to a .03 decline in the probability of leaving, from a baseline probability of .18. While the overall probability that a teacher leaves his or her current school at the end of the year is .18, it is only .15 among teachers 1 standard deviation above the mean of value added.

The table also shows that the likelihood that more effective teachers leave their school is even lower when they work in more effective schools—that is, the school-by-teacher value-added interactions are all negative and statistically significant for math. Each standard deviation increase in school value added further reduces by about 1 percent the probability that higher value-added teachers leave their school. For example, a 1 standard deviation increase in teacher value added reduces the probability of leaving by about 3 percent in schools of average effectiveness but decreases the probability of leaving by about 4 percent in schools that are 1 standard deviation above the mean of effectiveness. The interactions are also negative for reading value added but are not statistically significant. These findings hold across all three methods of computing teacher value added. The results are similar when we break teacher value added into quartiles. Here we find that the most effective schools (top quartile) are better able to keep their best (top quartile) teachers. They are not, however, differentially able to remove their least effective (bottom quartile) teachers. Using quartile measures, model 1 for math shows that teachers in the top quartile of value added who work in schools in the top quartile of school value added are 6 percent less likely to leave than top quartile teachers who work in less effective schools. These results hold across all versions of teacher

9. The findings discussed here are similar in direction when all teachers are included (i.e., experienced and novice) but smaller in magnitude and generally not statistically significant.

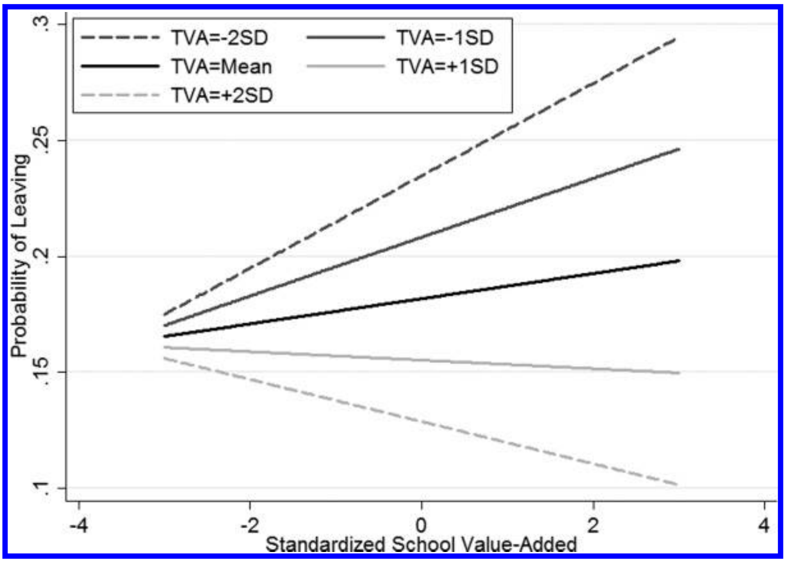

Figure 2. Probability of Leaving Current School by Teacher and School Value Added. Notes: The value-added measures for teachers and schools reflect value added to math achievement. The corresponding model is shown in column 3 of table 6. The probability that a teacher leaves his current school at the end of the year is predicted as a function of his own value added that year, the school's value added that year, an interaction between the two, a school fixed effect, and teacher-level control variables (race, gender, age, highest degree earned, experience in the district, and year dummies). The teacher-level control variables are set to their sample means.

value added for math and are in the expected direction but not statistically significant for reading.[10]

In figure 2 we graph the regression equation using continuous measures of teacher and school value added in math using the estimates from column 6 in table 6. We show the relationship between school value added and the probability that a teacher leaves his or her school at the end of the year for teachers at different levels of effectiveness. All other covariates are set to their sample means. The probability that low value-added teachers (those 2 standard deviations below the mean) leave their school is about .18 when they work in a low value-added school (those 2 standard deviations below the mean) but is about .27 when they work in a high value-added school (those 2 standard deviations above the mean). On the other hand, the probability that high value-added teachers leave their school at the end of the year is about .15 when they work in a low value-added school and about .11 when they work in a high value-added school.

10. In results not shown, we conduct these analyses separately for elementary schoolteachers and middle/high schoolteachers. The results are similar for both groups of teachers so we present only the pooled estimates here.

6. DISCUSSION

Not surprisingly, teachers in more effective schools demonstrate more positive career trajectories. The results presented above have shown that teachers in high value-added schools improve more rapidly from year to year. On average, in schools that are 1 standard deviation more effective, teachers' value added increases by up to 10 percent of a standard deviation more in a given year, though these results vary by specification. Effective schools also differentially retain more effective teachers. The odds that a teacher who is in the top quartile of effectiveness will leave in a given year is 30–40 percent lower in top quartile schools, though we do not find differential attrition of the least effective teachers relative to teachers demonstrating average value added in more effective schools. More effective schools also assign teachers to students more equitably. While novice teachers systematically teach students with lower entering test scores than their more senior colleagues, these relationships are approximately half as large in schools that are 1 standard deviation more effective. The analyses provide some evidence that schools are able to attract more effective teachers when teachers transfer across schools, though these results are not consistent.

Two caveats are warranted in interpreting these results. First, while in the same direction when effectiveness is defined in terms of value added to students' reading achievement as they are when value added is defined by math achievement, we found that the results for reading are not as consistently statistically different from zero. This is not the first study to find clearer effects for mathematics than for English language arts, but the difference is still worth noting.

The second caveat is that we have not attempted to identify the cause of the patterns we observe. While the more equitable assignment of teachers to classrooms is likely to be the result of school practices, we do not know whether these practices are driven by teachers or by the school leadership. The differential hiring of more effective transferring teachers might not even be driven by school practices. Teachers may be attracted to these schools because they are more effective. Similarly, less effective teachers may choose to leave these more effective schools not because they are encouraged to leave but because they feel out of place.

Nonetheless, while we cannot definitely attribute the patterns of recruitment, assignment, development, and retention to school leadership, the results suggest that school leadership and particular school personnel practices may be a driving force in effective schooling. Not only are school leaders responsible for personnel practices, but recent work has highlighted the importance of personnel practices and other organizational management practices for distinguishing (if not causing) effective schools (Grissom and Loeb 2011; Horng, Klasik, and Loeb 2010). This hypothesis is also consistent with the traditional Effective Schools research, which emphasizes the importance of school leadership (Sammons, Hillman, and Mortimore 1995). The results, moreover, are not surprising. Teachers strongly affect students' educational opportunities. Higher performing schools seem better able to build a staff of strong teachers through differential retention of good teachers, recruitment and hiring, and providing supports for teacher improvement. This article provides some empirical evidence that more effective schools are doing all three. In addition, these schools appear to use their teaching resources more efficiently, not assigning new teachers to lower performing students.

A slew of other articles have shown that teachers matter for student learning gains. However, the results of this study are novel in drawing attention to the multiple processes that together affect teachers and teaching—particularly teacher improvement, teacher retention, and effective use of teachers within the school. Improving teaching is not only about getting the best teachers in the school or keeping the better teachers once they are teaching—though the differential in the retention of more effective teachers between more and less effective schools is large. These retention dynamics are a feature of effective schools, but so are the supports that lead to teacher improvement, and so is the effective use of resources, as illustrated by the more equitable assignment of teachers to students. This article provides few direct insights into the practices associated with the observed relationships between personnel dynamics and student learning. That is for further work. It does suggest that this area would be a productive avenue both for expanding understanding of effective schooling and for school improvement itself.

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APPENDIX: BAYESIAN SHRINKAGE

Our estimated teacher effect ($\hat{\delta}_j$) is the sum of a “true” teacher effect (δ_j) plus some measurement error:[11]

$$\hat{\delta}_j = \delta_j + \varepsilon_{j.} \tag{A1}$$

The empirical Bayes estimate of a teacher’s effect is a weighted average of the estimated fixed effect and the average fixed effect in the population where the weight, λ_j, is a function of the precision of each teacher’s fixed effect and therefore varies by *j* and *t*. The less precise the estimate, the more we weight the mean. The more precise the estimate, the more we weight the estimate and the less we weight the mean. Similarly, the more variable the true score (holding the precision of the estimate constant), the less we weight the mean,

11. Here we make the classical errors in variables assumption, assuming that measurement error is not associated with an unobserved explanatory variable.

and the less variable the true score, the more we weight the mean, assuming the true score is probably close to the mean. The weight, λ_j, should give the proportion of the variance in what we observe that is due to the variance in the true score relative to the variance due to both the variance in the true score and the precision of the estimate. This more efficient estimator of teacher quality is generated by:

$$E(\delta_j|\hat{\delta}) = (1 - \lambda_j)(\bar{\delta}) + (\lambda_j) * \hat{\delta}_j, \tag{A2}$$

where

$$\lambda_j = \frac{(\sigma_\delta)^2}{(\sigma_{\varepsilon j})^2 + (\sigma_\delta)^2}. \tag{A3}$$

Thus the term λ_j can be interpreted as the proportion of total variation in the teacher effects that is attributable to true differences between teachers. The terms in equation A3 are unknown, so they are estimated with sample analogs.

$$(\hat{\sigma}_{\varepsilon j})^2 = \mathrm{var}(\hat{\delta}_{\varepsilon j}), \tag{A4}$$

which is the square of the standard error of the teacher fixed effects. The variance of the true fixed effect is determined by:

$$(\sigma_\delta)^2 = (\hat{\sigma}_\delta)^2 - mean(\hat{\sigma}_\varepsilon)^2, \tag{A5}$$

where $(\hat{\sigma}_\delta)^2$ is the variance of the estimated teacher fixed effects (Gordon, Kane, and Staiger 2006; Jacob and Lefgren 2005). We shrink the school value-added estimates in the same manner described above.

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