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Effective Schools

Managing the Recruitment, Development, and Retention of High-Quality Teachers

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ABSTRACT

Teachers are systematically sorted across schools. Often, schools serving the lowest-achieving students are staffed by the least-skilled teachers. While teachers' school preferences account for some of the sorting, school practices are also likely to be a key factor. Using value-added methods, the authors examine the relationship between a school's effectiveness during a given principal's tenure and the retention, recruitment and development of its teachers. Three key findings emerge about principal effectiveness. More effective principals: (1) are able to retain higher-quality teachers and remove less-effective teachers; (2) are able to attract and hire higher-quality teachers to fill vacancies; (3) have teachers who improve at a greater pace than those in schools with less effective leadership (there is some evidence for this, albeit weak). These findings reinforce the importance of personnel practices for effective school leadership.

INTRODUCTION

The literature on effective schools emphasizes the importance of a quality teaching force and strong leadership in improving educational outcomes for all students (Mortimore, 1993; Brewer, 1993; Sammons, Hillman, and Mortimore, 1995; Taylor, Pearson, Clark and Walpole, 2000). The important effect of teachers on student achievement is particularly well established (e.g. Rockoff, 2004). However, 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 (Scafidi, Stinebrickner, and Sjoquist, 2003; Hanushek, Kain, and Rivkin, 2004; Boyd, Lankford, Loeb, and Wyckoff, 2005 and 2005b); however, school leadership also strongly affects teachers' career decisions (Boyd, Grossman, Ing, Lankford, Loeb, and Wyckoff, 2009).

In this paper, we examine whether some schools are better able to recruit and retain high quality teachers and help teachers improve over time. Our primary question asks whether more effective schools are more likely to retain more effective teachers and remove less effective ones. We also ask whether more effective schools are more likely to attract highly-effective teachers for vacant positions and whether they better support teacher improvement over time. If the answers to these questions are yes, then there is likely to be a Matthew effect in regards to school quality. That is, principals at highly effective schools are better able to staff their schools with high quality teachers, in turn making these schools more effective.

To answer these questions, we use six 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 a measure of schools' effectiveness during each principal's tenure. We define school effectiveness based on their leadership because principals hold formal authority in any given school and are likely to be responsible for school-level personnel practices. Indeed, the empirical literature suggests that good principals take a pro-active stand in the recruitment of the teaching force at their school (Brewer, 1993; Levine and Lezotte, 1990). Our measure of schools' effectiveness, based on a value-added to student achievement during a principal’s tenure, aims to isolate leadership effectiveness. We call this measure “principal effectiveness” because of its link to the principal’s time at the school; even though some of what we call principal effectiveness will be due to the actions of other leaders in the school and the state of the school when the principal arrived. We also construct a similar measure for teacher effectiveness based on value-added by a teacher to student achievement, and use these two effectiveness measures to better understand the importance of personnel practices for school effectiveness.

Our results reveal three key findings. First, we find that more effective principals, as measured by schools' value-added to student achievement, are able to retain more effective teachers and remove less effective teachers. We find that teachers who are above the mean of teacher value-added are substantially less likely to transfer from more effective principals. Conversely, teachers who are below the mean of teacher value-added are substantially more likely to transfer from schools with more effective principals. Second, among teachers who transfer, we find that higher value-added teachers are more likely to transfer to schools with effective leadership. This result provides some evidence that principals are not only able to retain effective teachers but are able to attract them as well. Third, we find some, albeit weak, evidence that teachers’ value-added improves more over time when they work for more effective principals, however these results are sensitive to model specification.

BACKGROUND

The Coleman Report (1966) raised doubts about the ability of schools to improve student learning outcomes by arguing that student background and socioeconomic status are much more important in determining educational outcomes than are measured differences in school resources (*i.e.,* per pupil spending). The ability to measure differences in school inputs, both financial and non-financial, has advanced considerably and together with sophisticated analytical techniques, subsequent literature has been able to show that schools can contribute to student learning. This body of work, initially termed the "Effective Schools Literature" identifies multiple features of effective schools. Although the quality of the teaching force remains salient throughout this literature, leadership is also considered a key component of effective schools and improving school outcomes (Baker and Cooper 2005, Branch et al. 2008, Brewer 1993, Eberts and Stone 1988). Not surprisingly, research also shows that these two components of effective schools – teachers and school leaders – are linked. For example, studies find that principals' leadership (or lack thereof) often determines whether teachers are satisfied with their jobs and whether they stay (Johnson and Birkeland, 2003; Useem, 2003; Boyd et al., 2009).

Researchers have attempted to understand what effective principals *do* to improve school outcomes. Two perspectives have dominated the study of principal roles: instructional leadership and transformational leadership. Instructional leadership theory focuses on the principal's role in aiding and monitoring the school's instructional program and developing a positive learning culture (Hallinger and Murphy, 1985; Heck, 1992). In contrast, transformational leadership focuses on increasing the organization's capacity to innovate – that is, to adapt to change successfully (Bass, 1998). The literature is divided on which perspective is superior, with some studies arguing for the importance of instructional leadership on schooling outcomes, and others for the importance of transformational leadership. Scholars have also argued for approaches which combine the two theories of leadership (Marks and Printy, 2003).

Grissom and Loeb (2009) depart from an emphasis on leadership orientations and beliefs to a focus on actions and skills. They use survey data on principals' self-reports of effectiveness, triangulated with assistant principals' assessments of their principal's effectiveness, and find that principals' organization management skills consistently predict student achievement growth and other measures of school success. In contrast, the other principal skill domains they identified – instruction management, internal relations, administration, and external relations – were not associated with measures of school success. Similarly, Horng, Klasik, and Loeb (forthcoming) use observational data on principal time use and find a positive relationship between time spent on organization management tasks, such as hiring and budget allocation, and school effectiveness.

Building on this body of work, we focus on a specific aspect of organization management: the hiring and retention of effective teachers and the counseling-out of ineffective teachers. While principals appear important for teacher retention, little research has examined variability in the ability of principals to retain or hire effective teachers. Brewer (1993) finds some evidence to suggest that the greater the percentage of teachers appointed by principals with high academic goals, the higher the student test score gains. Whether the principal had high (or low) academic goals was determined by the principal's ranking of academic excellence as a high (or low) school goal. Using cross-sectional administrative data from Pennsylvania, Strauss (2003) also finds evidence to suggest that principals can affect student achievement indirectly through the teacher hiring process.

We add to this body of work by examining whether more effective principals – as defined by student achievement at schools during a principal's tenure – are better able to attract and retain more effective teachers as well as remove less-effective ones. The effectiveness of school leadership in the studies cited above is generally measured through principals' reports of their own effectiveness or staff reports of their principals' effectiveness. Although illuminating, these measures of effectiveness are likely to suffer from considerable measurement error and reporting bias, making the conclusions drawn from them less reliable. Further, these measures of principal effectiveness are based on cross-sectional data, limiting their use in causal inference. One exception to the use of self-reports or staff reports to measure effectiveness are the value-added methods used by Branch, Hanushek and Rivkin (2008). They use principals' value-added to student achievement measured over multiple years to capture a principal's contribution to student test-score gains and, thus, principal effectiveness. We build on Branch et. al. (2008) and use panel data on students, teachers and principals to create value-added measures of effectiveness. We then use these measures to examine the relationship between principal effectiveness and teacher recruitment, retention and development.

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 2003-04 through the 2008-09 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 and principals observed over a six-year time frame, the data provide substantial variation for examining differences in principal effectiveness.

We use a measure of principal effectiveness based on student achievement gains in math and reading at a school during a given principal's tenure. 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 only use math and reading tests in our analyses. The FCAT includes criterion referenced tests measuring selected benchmarks from the Sunshine State Standards (SSS). We standardize students' test scores to have a mean of zero and a standard deviation of one within each grade and school-year. By using the same standardization in all grades, we preserve the comparability of scores across grades.

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 the percent of minority students, the percent of students receiving free or reduced priced 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. After linking the M-DCPS student and staff data, we construct a measure of principal effectiveness based on student achievement in math and reading at a school during a given principal's tenure.

Table 1 lists the mean and standard deviations of all variables used in our analyses. There are 351,888 unique 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/reduced priced lunches. Principals have been a principal in the district for an average of approximately three years and have served as principal at their current school for almost two years. Principals are 48 years old on average, and 65 percent have master's degrees. We were able to compute value-added estimates for 6200 teachers who taught students who were tested in math and reading. These teachers average approximately six years of experience in the district, are predominately female (85 percent) and their racial composition is similar to that of students and principals in that most are Hispanic.

Estimating Value-Added

We begin by estimating schools' value-added to student achievement for each principal, which we use as our proxy of principal effectiveness. The estimation is based on the following equation:

$$A_{isjt} - A_{isj(t-1)} = \beta X_{it} + \delta_j + Pexp_{jt} + \eta C_t + \mu S_t + \pi_g + \pi_t + \pi_i + \varepsilon_{ijt} \quad (1)$$

The outcome (A_{isjt}) is the test score of student *i* in school *s* with principal *j* in year *t* minus the student's test score in the same subject in the prior year. The achievement gain is predicted as a function of time-varying student characteristics such as free or reduced price lunch receipt and grade retention (X_{it}), principal experience ($Pexp_{jt}$), current year classroom characteristics (e.g., percent minority, percent receiving free or reduced lunch, average prior achievement) (C_t), current year school characteristics (e.g., percent minority, percent receiving free/reduced lunch, average prior achievement) (S_t) fixed effects for grades, years, and students (π_g, π_t, π_i), and a principal fixed effect (δ_j) . The coefficients on the principal fixed effects which we shrink to account for measurement error are our measures of value-added.

The test scores are the scaled scores from the FCAT, standardized to have a mean of zero and a standard deviation of one for each grade in each year. Subscripts for subjects are omitted for simplicity but we estimate this equation separately for math and reading. Principal experience is entered as dummy variables and top coded at 10 or more years of experience. The measures refer to the total number of years the individual has been a principal in the district. Since we use a lagged test score to construct our dependent variables, 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.

We are unable, and do not attempt, to separate principal from teacher effects in these models. The estimate of principal effectiveness captures the quality of the teaching force at a school. Since principals are likely to influence student learning indirectly through the recruitment, retention, assignment, and development of teachers at their school, including teacher characteristics or teacher fixed effects in the principal value-added estimation would remove the variation in principal effectiveness that we seek to capture. In addition, because all students are in classrooms, there is no variation in student learning that can be attributed to the school once classroom learning is accounted for.

We estimate multiple variations of Equation 1 in order to get alternative measures of school value-added associated with each principal. Appendix 1 describes these variations in detail. One set of variations removes the student fixed effects from Equation 1, and thus identifies effectiveness largely from differences between observationally similar schools. In contrast the model in Equation 1 identifies the value-added from differences in achievement gains for a given student assigned to different principals in different years. A second variation for creating effectiveness measures substitutes the student fixed effects in Equation 1 for school fixed effects and thus identifies effectiveness by comparing principals who work at the same school. For each of these three approaches - neither student nor school fixed effects, school fixed effects, and student fixed effects - we estimate average value-added across all years that a principal appears in the data and we also estimate value-added separately by year.

Each method has strengths and weaknesses. Models with student fixed effects are appealing because they allow us to examine differences in learning within the same students in years they attend schools with different principals. These models account for all unobserved time invariant attributes of students that may be associated with learning. In the same way, including school fixed effects helps control for unobservable differences among schools that may be associated with learning. However, models with school fixed effects can only be identified for principals who switch schools. Turnover rates among principals are fairly high as shown in Table 2 with about 15 to 20 percent of principals transferring to another school in the district each year. Even though mobility among principals is not uncommon in M-DCPS, we lose about 40 percent of principals when including school fixed effects. Since mobility is not random and may be more common among certain types of principals serving certain types of schools, omitting non-mobile principals reduces the representativeness of our sample.[1]

After estimating Equation 1 we save the principal fixed effects and their corresponding standard errors. The estimated coefficients for the principal fixed effects include measurement error as well as real differences in achievement gains associated with principals. We therefore shrink the estimates using the empirical Bayes method to bring imprecise estimates closer to the mean (see Appendix 2).

Table 3 gives the correlations among the primary measures of effectiveness - no fixed effects, school fixed effects, and student fixed effects for math and reading separately. The table shows that the samples for the school fixed-effect models are far smaller than those for the other specifications. It also shows that while the student fixed-effect measures and the no fixed-effect measures are strongly correlated, the school fixed-effects variables are not. In fact, there is very little correlation between math and reading effectiveness using the school fixed-effect specifications. These results lead us to believe that there is not enough variation in the school fixed-effect models to accurately estimate the differential effectiveness of the school during each principal's tenure. As such, we focus our analyses on the student fixed-effect specification, which has theoretical benefits relative to the no fixed-effect approach, but we also run specification checks with the alternative models.[2]

We analyze the relationship between principal effectiveness and teacher turnover in the aggregate but we are primarily interested in examining whether effective schools are differentially able

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[1] Appendix 1 describes the alternate methods used in the various model specifications. We focus our discussion on estimates from models with student fixed effects which are described in columns 3 and 6 of the Appendix 1.
[2] Appendix 1 includes plots of the distributions of the effectiveness measures.

to keep effective teachers and remove ineffective teachers. In order to address this question we generate a measure of teacher effectiveness using a similar approach to the one described in Equation 1. We re-estimate Equation 1, substituting principal experience with teacher experience, and replacing the principal fixed effects with teacher fixed effects. Teacher experience is entered as a dummy variable and top coded at 10 or more years of experience. It refers to the total number of years the teacher has worked in the district. In the middle and high school years, teaching experience refers to the experience of the teacher in the subject tested.

We shrink the teacher fixed effects using the empirical Bayes method described in Appendix 2. There is greater imprecision in our estimates of teacher value-added than principal value-added since teachers' class sizes are smaller than the total school enrollment attributed to a principal. Consequently, shrinking the principal fixed effects tends not to change the estimates very much but does change the teacher fixed effects measures. In addition 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 10 students in a given year.

Teacher value-added as measured by student achievement on state tests is clearly not a perfect measure of teacher effectiveness. On the positive side, this measure adjusts for a rich set of student and classroom characteristics. Recent research also has demonstrated that higher value-added teachers, as measured in this way, tend to exhibit stronger classroom practices as measured by observational protocol such at the Classroom Assessment Scoring System (CLASS) (Pianta, LaParo, and Stuhlman, 2004) and Protocol for Language Arts Teaching Observation (PLATO) (Boyd, et. al. 2009). However, there is clearly measurement error in our estimates of teacher value-added 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 as well covered by the standardized tests.

METHODS

This study asks three questions: (1) to what extent do more effective principals retain more effective teachers? (2) to what extent do more effective principals hire more effective teachers? and (3) to what extent do teachers improve more with experience in schools with more effective principals?

Retention

To study the association between teacher turnover and principal effectiveness, we estimate multinomial logit models predicting whether a teacher stays in the same school, transfers to another school in the district, or attrits from the district at the end of each year as a function of principal value-added and other teacher, principal and school-level controls. Equation 2 describes the model:

$$P\left(Y_{ist} = j \mid X_{ist}\right) = \frac{exp(X_{ist}\beta)}{1 + \Sigma_1^j exp(X_{ist}\beta)} \text{, where } X_{ist}\beta = T_{ist}\beta_1 + S_{st}\beta_2 + PE_{st}\beta_2 + (PE_{st} \times TE_{ist})\beta_3 + \varepsilon_{ist} \qquad (2)$$

The probability that teacher *i* in school *s* in time *t* will choose career option *j* is a function of the teacher's own characteristics, *T*, which includes his or her effectiveness, the school's characteristics, *S*, the principal's effectiveness, *PE*, and the interaction between the principal's effectiveness and the teacher's effectiveness. The coefficient on the interaction in this model, β_3, tells us whether there are differential career paths for teachers as a function of the principal's effectiveness.

One concern with using both principal and teacher effectiveness in the same model is the issue of circularity. A model that includes teacher and principal value-added measured in the same period makes the causal ordering of these measures ambiguous. In the teacher turnover analyses, for example, we want to test whether more effective principals 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 principals or schools look like they have higher value-added only because they have kept particularly good teachers. For example if we estimated school value-added in the year after the less-effective teachers had left and the more effective teacher had stayed, the school would look more effective regardless of its practices in the prior years that led to this differential turnover. To address this issue, we use re-estimate our the model in Equation 2 using an alternative measure of principal effectiveness that is the average of each principal's effectiveness in the years prior to the teacher's transition. While the year-by-year measures of principal effectiveness are less precise than the measure averaged over all years, the value-added based on prior years allows us to examine how principal effectiveness in a given period influences teacher turnover behavior in a subsequent period and helps us avoid the circularity problem described above. Using this lag assures that we will not be attributing the benefits of having a better teacher stay to the measurement of principal effectiveness.

We also use two different measures of teacher value-added in our models. The first is just the average of a teacher's value-added over all years. The shortcoming of this measure for our turnover models is that included in its estimation are years after a teacher's turnover decision. This is a problem if, for example, transferring teachers get better (or worse) in their new school. To make the temporal ordering more clear we also use an alternate measure of teacher value-added that varies by year. We take the mean of this measure using all years through the year in which the teacher is making a transfer decision. Though this is our preferred measure theoretically, imprecision in our estimates of teacher value-added by year make us cautious in our interpretation of estimates based on this measure.

Recruitment and Hiring

In addition to removing ineffective teachers and retaining effective ones, effective principals may also hire more effective teachers when vacancies arise. In order to examine this issue, our next set of models is restricted to teachers who transfer and examines the transfer destinations of teachers to see whether higher value-added teachers tend to transfer to schools with more effective principals.[3] In keeping with the discussion above, in one set of specifications, we use the average principal effectiveness measure across all years of available data, and in another set we use value-added by year for the year prior to the teacher's transfer decision. The latter is less precisely measured but does not have the potential to identify effective principals based on their hiring more effective teachers alone. We estimate the following equation, restricting the analysis to teachers who transfer:

$$PE_{ist} = \alpha + T_{ist}\beta_1 + S_{st}\beta_2 + P_{st}\beta_3 + \beta_4(\mathrm{TE}_i) + \varepsilon_{ist} \qquad (3)$$

where *T, S,* and *P* are attributes of schools, teachers, and principals measured in the current year. *TE* is the effectiveness of teacher *i* and *PE* is the effectiveness of the principal in the school that the teacher transfers to in year *t*.

Teacher Development

Our final set of models tests whether the value-added of teachers changes more when they are in a school with an effective principal. We regress teacher value-added in the current year on teacher value-added in the prior year and principal value-added. Since we control for the lag of teacher value-added,

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[3] Teachers who transfer are systematically different than 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 masters' degree (36 percent vs. 40 percent). However, we do not find a statistically significant difference between those who transfer and other teachers in their value-added estimate for either math or reading.

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 and teacher experience which is entered as dummy variables top-coded at 20 years. We use a measure of principal effectiveness that combines all years prior to (t-1) so that the effectiveness of a teacher in the current and prior year (which are both in the model) are not co-estimated with the measure of principal effectiveness. The model is shown by the following equation:

$$TE_{ist} = \alpha + (\beta_1 TE_{is(t\text{-}1)}) + \beta_2 (PE_{st}) + (Texp_{ist})\beta_3 + \pi_t + \varepsilon_{ist} \quad (4)$$

where TE_{it} is teacher effectiveness in the current year, TE_{t-1} is teacher effectiveness in the prior year, PE_{st} is the mean of principal effectiveness in t-2 and all prior years, $Texp$ are dummy variables for teacher experience (top coded at 20 or more years) and π_t are year fixed effects.

FINDINGS

Retention

In Table 4 we present results from multinomial logit models that regress teacher retention on principal effectiveness. The likelihood of transferring to a new school and attriting from the district are compared to staying in the same school (the reference category). We first run the models using our measure of principal effectiveness averaged over all years and then repeat the analyses using principal value-added only in the prior years. All models include controls for teacher, school and principal characteristics. We find no evidence of an association between principal value-added and teacher turnover, overall, as shown in columns one and three. However, we are primarily interested in the relationship between principal effectiveness and the differential attrition of effective teachers. Columns two of Table 4 introduce teacher value-added into the model. The negative coefficient for transferring in the math equation demonstrates that higher value-added teachers are less likely to transfer across schools. This result is in keeping with prior studies of teacher attrition (Boyd et al., 2009c; Goldhaber, Gross and

Player, 2007; Hanushek, Kain, O'Brien and Rivkin, 2005). Not all the coefficients on teacher value-added in the transferring equations are significant, but they are negative across all specifications.

To explore the relationship between principal and teacher effectiveness, we interact teacher and principal value-added and report the results in columns three of Table 4. Across all specifications of the model, the interaction negatively predicts teacher transfer. The results suggest that the likelihood that a more effective teacher will transfer declines as principal effectiveness increases. Conversely, the likelihood that a less effective teacher will transfer increases as principal effectiveness increases.

To more clearly illustrate these results, we graph the results from model 3 in the second panel in Table 4 in Figure 1 (math) and Figure 2 (reading). We plot the predicted probability that a teacher stays in the same school as a function of principal value-added. Each graph includes five different lines which show the relationship between principal value-added and retention for teachers at different levels of effectiveness. Other covariates in the model are set to their sample means. There is essentially no relationship between principal value-added and teacher turnover among teachers who are of average effectiveness (shown by the solid black line). However, the relationship between principal value-added and the probability of staying in the same school is positive for teachers who are one or two standard deviations above the mean of effectiveness and negative for teachers who are one or two standard deviations below the mean of effectiveness.

For example, Figure 2 shows that the probability that a highly effective teacher (i.e., someone that is 2 standard deviations above the mean of effectiveness) will stay at their current school is about .86 at the lower end of the principal value-added distribution and about .94 at the higher end (shown by the solid light grey line). On the other hand, the probability that a less effective teacher (i.e., someone that is 2 standard deviations below the mean of effectiveness) will stay at their current school is about

.96 at the lower end of the principal value-added distribution but only .84 at the higher end (shown by the dashed light grey line).[4]

To check the robustness of these findings, we estimate alternate models with fixed effects to examine the relationship between teacher turnover and principal value-added. Table 5 shows these results. Columns one and four include principals fixed effects while columns two and three include school fixed effects. The models get us closer to isolating causal effects by accounting for the non-random sorting of principals and teachers across schools, since fixed effects allow us to control for all time-invariant and unobserved factors affecting outcomes. For simplicity, we use as the outcome a dichotomous variable indicating whether or not the teacher leaves their school after the current school year, either via a transfer or attrition from the district. The results for the models without the interaction term are essentially unchanged by adding a school fixed effect.

There is no evident relationship between principal value-added and turnover. Within schools and within principals higher value-added teachers are less likely to leave than are lower value-added teachers. Overall, the models with the interactions yield similar results to those presented previously. Column 2 shows that effective teachers are less likely to leave and less effective teachers are more likely to leave even within schools. Column 4 reveals the same finding suggesting that within principals those that are more effective are simultaneously able to keep good teachers and get rid of bad ones. Only the results for effectiveness as measured by reading value-added are statistically significant.

[4] In results not shown in Table 4, we re-estimate the models using teacher value-added only in previous years. The coefficients on the interaction between teacher and principal effectiveness continue to be significant but they estimates are not statistically distinguishable from zero. We test whether teachers' value-added is higher in the schools they transfer to and again find that the difference is not statistically distinguishable from zero. Our estimates of teacher value-added in a single year are not precise enough to estimate this effect precisely.

Recruitment and Hiring

In addition to removing ineffective teachers and retaining effective ones, more effective principals may also hire higher value-added teachers when vacancies arise. This differential hiring may be driven by pro-active recruitment efforts by such principals or by teachers' preferences for more effective schools. While we can't separate the possible mechanisms, Table 6 shows some evidence of differential hiring. We take all instances of teacher transfers and regress the value-added of the principal in the school to which they transfer on teacher value-added. We try multiple specifications in keeping with the analyses described above, first using a measure of average principal and teacher value-added and then using a measure of average teacher value-added and principal value-added in the years prior to the teacher's transfer decision. The coefficients are positive across all specifications suggesting that higher value-added teachers tend to transfer to higher value-added principals. For example, model 2 (which includes principal, school, and teacher controls) for reading value-added shows that a one standard deviation increase in the value-added of a transferring teacher is associated with about a .11 increase in the standard deviation of the value-added of the principal at the school to which they are transferring.

Taken together, these findings suggest that more effective teachers tend to move to schools with higher value-added principals. As a caveat, the estimates do not hold up to a specification check that uses only teachers' prior value-added.[5] We do not find a significant difference in teacher value-added before and after their transfer, so the lack of significance is likely driven by measurement error in the yearly value-added estimates.

Teacher Development

In our final set of results, we investigate whether teachers benefit from being in schools led by effective principals. Table 7 provides the results of these specifications. We test the relationship between the

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[5] These results do hold for the measure of principal effectiveness based on models without student fixed-effects.

change in teacher value-added and principal effectiveness using the effectiveness of the principal that the teacher worked with in the current year as measured by that principal's effectiveness in all years prior to year (t-1). We worry that because the teacher's value-added in the prior year is also in the model that the teacher and principal measures were estimated on the same data and thus the effects might be circular. We find a robust relationship between principal effectiveness and teacher learning when value-added is measured by math test performance, but not when value-added is measured by reading performance.[6] These results suggest that more effective principals may be able to "develop" the teachers who work in their schools. However, the results aren't as robust as those for retention and recruitment. In addition to estimating these models for all teachers, we also estimate them only for teachers who are in their first three years in the district. The results are similar for all teachers and for new teachers. The results are not sensitive to the exclusion of teachers who change schools or principals across years or to the exclusion of teachers in schools with first year principals.

DISCUSSION

The analyses presented in this paper suggest that personnel management practices play an important role in highly effective schools. Principals at schools which have shown prior growth in student achievement appear to be better able to attract and retain high quality teachers and remove low quality teachers. We also find some, albeit weak, evidence that teachers in schools with more effective principals improve more over time. These results are further evidence of the importance of organization management for school leadership (Grissom and Loeb, 2009; Horng, Loeb and Klasik, forthcoming). The results are also not surprising. Teachers strongly affect students' educational opportunities. A key role of school leadership is to staff the school with strong teachers and they can do this through differential

[6] Again these results hold for the measure of principal effectiveness based on models without student fixed-effects. However, they do not hold up to principal effectiveness measured contemporaneously with the teacher value-added.

retention of good teachers, through recruitment and hiring, and through providing supports for teacher improvement. This paper provides some empirical evidence that more effective principals are doing all three.

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Figures and Tables

Figure 1. Teacher Probability of Staying in Same School:
Teacher and School Value-Added in Math

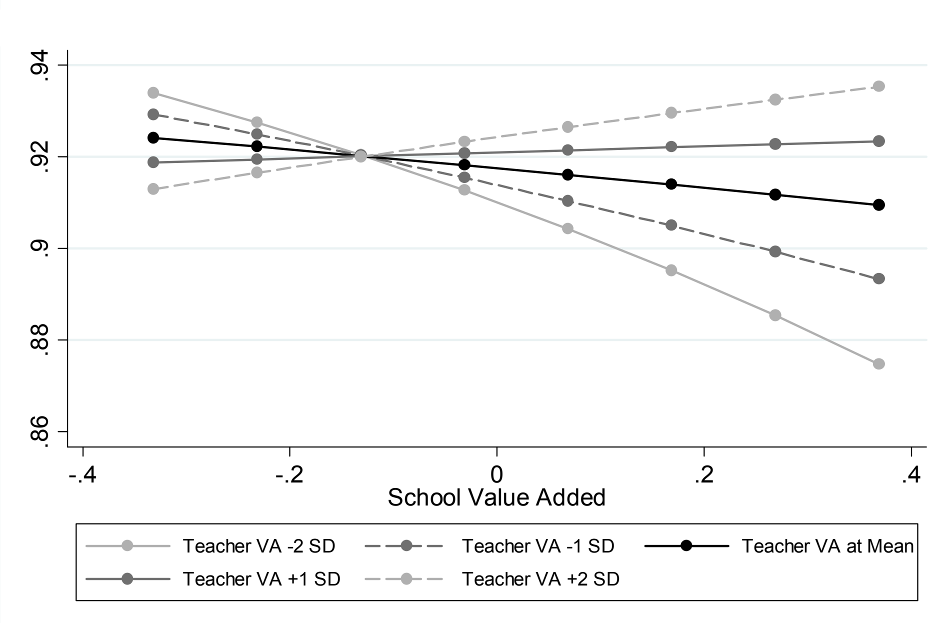


Figure 2. Teacher Probability of Staying in Same School:
Teacher and School Value-Added in Reading

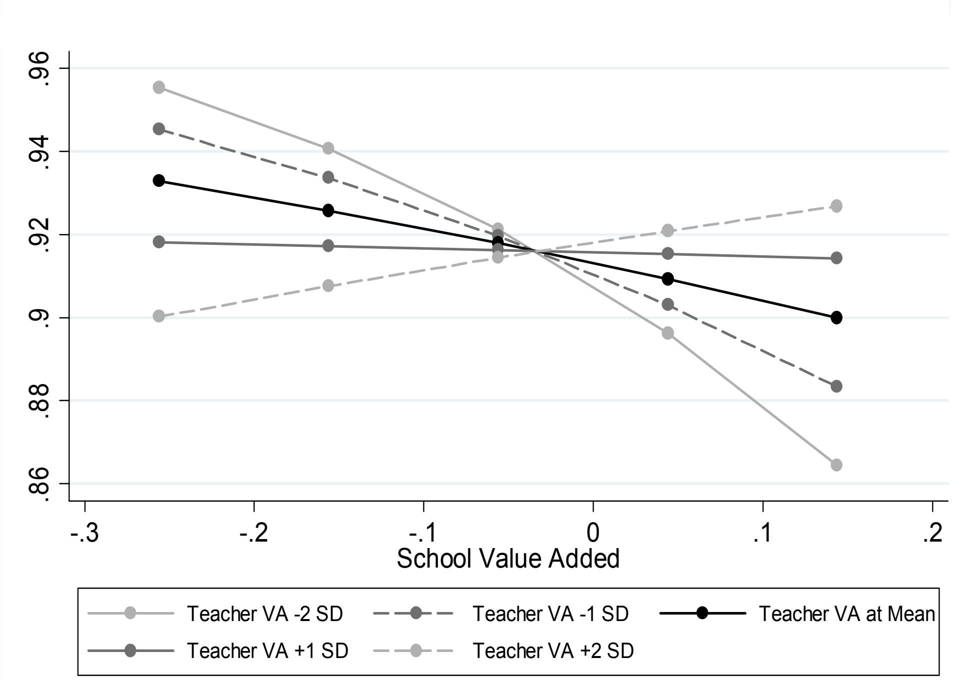


Table 1. Descriptive Statistics

	Mean	SD
Student Characteristics		
Standardized Math Score	-0.006	0.998
Standardized Reading Score	-0.095	0.997
Black	0.268	
Hispanic	0.613	
Female	0.498	
Limited English Proficient	0.088	
Retained in Year Prior	0.066	
Eligible for Subsidized Lunch	0.614	
Total Student Observations (with test scores)	880946	
Unique Students (with test scores)	351888	
Average Number of Observations Per Student	3	
Principal Characteristics		
Value-Added in Math (Average)	0.046	0.1
Value-Added in Reading (Average)	0.003	0.08
Value-Added in Math (by Year)	-0.044	0.22
Value-Added in Reading (by Year)	0.005	0.18
Years as Principal in the District	2.763	3.37
Years as Principal at Current School	1.88	2.71
Black	0.353	
Hispanic	0.395	
Female	0.685	
Age	47.96	7.96
Master's Degree or Higher	0.647	0.48
Number of Principals	473	
Teacher Characteristics (Among Those With Value-Added)		
Value-Added in Math	0.032	0.207
Value-Added in Reading	0.191	0.145
Years in District	6.247	6.908
Black	0.311	
Hispanic	0.403	
Female	0.852	
Age	38.259	11.191
Master's Degree or Higher	0.355	0.479
Number of Teacher Observations	20000	
Number of Teachers	6200	
School Characteristics (in 2008)		
Percent Eligible for Subsidized Lunch	0.669	0.233
Percent Minority (Black or Hispanic)	0.893	0.121
Percent Achievement Level 1 (Low Achieving) in Math	0.184	0.151
Percent Achievement Level 1 (Low Achieving) in Reading	0.244	0.17
Student Enrollment	819	688
Elementary School	0.476	
Middle School	0.24	
High School	0.189	
Number of Schools	422	

Table 2. Annual Turnover Rate Among Principals

	Left District	Transferred Schools	Same School
2004	3.73	18.64	77.63
2005	5.98	15.28	78.74
2006	5.86	19.22	74.92
2007	8.06	15.48	76.45
Total	5.94	17.15	76.92

Table 3. Correlations Among Different Fixed Effects Estimates
(Using Standardized EB Shrunken FE)

	No FE		School FE		Student FE	
	Math	*ELA*	*Math*	*ELA*	*Math*	*ELA*
No FE	N=470					
Math	1.00					
ELA	0.72***	1.00				
School FE	N=270	N=270				
Math	0.27***	0.16**	1.00			
ELA	0.09	0.19***	-0.12	1.00		
Student FE	N=470	N=470	N=270	N=270		
Math	0.81***	0.64***	0.27***	0.10	1.00	
ELA	0.56***	0.73***	0.14*	0.17*	0.72***	1.00

Table 4. Multinomial Logit Models of Teacher Turnover by Principal Value-Added (Reference = Stayed in Same School)

	Teacher Left District			***Teacher Transferred Schools***		
	1	2	3	1	2	3
OVERALL AVERAGE PVA AND TVA						
Math Value Added						
Principal Value Added	-0.065	0.012	0.010	0.078	0.200	0.217
	(0.446)	(0.454)	(0.455)	(0.437)	(0.449)	(0.447)
Teacher Value Added		-0.198	-0.221		-0.341 *	-0.236
		(0.175)	(0.206)		(0.146)	(0.178)
Principal*Teacher Value Added			0.327			-1.812
			(1.644)			(1.626)
N	17893	17893	17893	17893	17893	17893
Reading Value Added						
Principal Value-Added in Reading	-0.754	-0.824	-0.765	0.956 +	1.060 +	2.376 **
	(0.491)	(0.506)	(0.758)	(0.568)	(0.583)	(0.781)
Teacher Value Added		0.164	0.164		-0.278	-0.240
		(0.231)	(0.230)		(0.200)	(0.199)
Principal*Teacher Value Added			-0.319			-7.218 *
			(3.348)			(3.321)
N	20230	20230	20230	20230	20230	20230
Teacher Characteristics	X	X	X	X	X	X
School Characteristics	X	X	X	X	X	X
Principal Characteristics	X	X	X	X	X	X
Robust Stand Errors (by Principal)	X	X	X	X	X	X

Table 4, continued

OVERALL AVERAGE TVA, CUMULATIVE AVERAGE PVA FOR ALL YEARS THROUGH t-1

Math Value Added						
Principal Value Added	0.173	0.215	0.192	0.044	0.083	0.177
	(0.339)	(0.344)	(0.353)	(0.424)	(0.433)	(0.426)
Teacher Value Added		-0.222	-0.157		-0.195	-0.484 +
		(0.217)	(0.232)		(0.206)	(0.257)
Principal*Teacher Value Added			0.737			-2.715 +
			(1.102)			(1.516)
N	9581	9581	9581	9581	9581	9581
Reading Value Added						
Principal Value-Added in Reading	-0.607	-0.617	-0.296	1.800 **	1.884 **	3.249 ***
	(0.467)	(0.481)	(0.698)	(0.657)	(0.654)	(0.840)
Teacher Value Added		0.042	-0.146		-0.336	-1.168 **
		(0.295)	(0.425)		(0.292)	(0.405)
Principal*Teacher Value Added			-1.603			-6.900 **
			(2.735)			(2.428)
N	10910	10910	10910	10910	10910	10910
Teacher Characteristics	X	X	X	X	X	X
School Characteristics	X	X	X	X	X	X
Principal Characteristics	X	X	X	X	X	X
Robust Stand Errors (by Principal)	X	X	X	X	X	X

Table 5. Logit Models of Teacher Turnover by Principal and Teacher Value-Added with Fixed Effects

	1		2		3		4	
OVERALL AVERAGE PVA AND TVA								
Math Value Added								
Principal Value Added	-0.939		-0.884					
	(0.607)		(0.608)					
Teacher Value Added	-0.455	***	-0.331	*	-0.413	***	-0.291	*
	(0.114)		(0.141)		(0.115)		(0.144)	
Principal*Teacher Value Added			-1.961				-1.928	
			(1.301)				(1.345)	
N	18123		18123		17585		17585	
Reading Value Added								
Pricipal Value-Added in Reading	1.101		2.736	**				
	(0.736)		(0.867)					
Teacher Value Added	-0.180		-0.120		-0.136		-0.093	
	(0.153)		(0.155)		(0.155)		(0.156)	
Principal*Teacher Value Added			-8.012	***			-7.117	**
			(2.260)				(2.324)	
N	20559		20559		19897		19897	
OVERALL AVERAGE TVA, CUMULATIVE AVERAGE PVA FOR ALL YEARS THROUGH t-1								
Math Value Added								
Principal Value Added	-0.184		-0.141		-0.314		-0.230	
	(0.557)		(0.559)		(0.896)		(0.898)	
Teacher Value Added	-0.386	*	-0.482	*	-0.357	*	-0.491	**
	(0.160)		(0.188)		(0.162)		(0.190)	
Principal*Teacher Value Added			-0.973				-1.396	
			(0.988)				(1.018)	
N	9475		9475		9138		9138	
Reading Value Added								
Principal Value-Added in Reading	0.375		1.330		0.606		1.627	
	(0.772)		(0.854)		(1.144)		(1.208)	
Teacher Value Added	-0.158		-0.735	*	-0.170		-0.745	*
	(0.205)		(0.305)		(0.207)		(0.305)	
Principal*Teacher Value Added			-4.702	**			-4.821	**
			(1.809)				(1.843)	
N	10966		10966		10575		10575	
School Fixed Effect	—		X		X		—	
Principal Fixed Effect	X		—		—		X	
Teacher Characteristics	X		X		X		X	
School Characteristics	X		—		—		X	
Principal Characteristics	—		X		X		—	

Note: In the top panel, in model 4 the main effect on principal value-added is absorbed by the principal fixed effect.

Table 6. Predicting Principal Value-Added of the Schools to Which Teachers Transfer
(Only Includes Teachers who Transfer)

	Principal Reading VA				Principal Math VA			
	1		2		1		2	
Overall Average TVA and PVA								
Teacher Value Added	0.112	***	0.073	***	0.075	***	0.043	**
	(0.015)		(0.013)		(0.013)		(0.013)	
N	1542		1542		1340		1340	
Overall Average TVA, Cumulative Average PVA up Through Year Prior to Teacher's Transfer								
Teacher Value Added	0.088	***	0.049	*	0.092	**	0.031	
	(0.025)		(0.021)		(0.028)		(0.029)	
N	1149		1149		982		982	
Teacher Controls	---		X		---		X	
Current School Controls	---		X		---		X	
Current Principal Controls	---		X		---		X	

Standard errors are clustered at the principal level.

Table 7. Gains in Teacher Value-Added by Principal Value-Added

	Math		Reading	
All Teachers, Regardless of Transfer				
All Teachers				
Teacher Value-Added in Prior Year	0.000		0.000	+
	(0.000)		(0.000)	
Principal Value	0.338	***	-0.217	
	(0.048)		(0.206)	
N (Observations)	1843		1944	
New Teachers (3yrs or less exp)				
Teacher Value-Added in Prior Year	-0.001		-0.002	
	(0.001)		(0.004)	
Principal Value Added	0.244	**	0.006	
	(0.075)		(0.359)	
N (Observations)	517		548	
Teachers in Same School in Year t and t-1				
All Teachers				
Teacher Value-Added in Prior Year	0.000		0.000	+
	(0.000)		(0.000)	
Principal Value Added	0.347	***	-0.203	
	(0.049)		(0.211)	
N (Observations)	1757		1865	
New Teachers (3yrs or less exp)				
Teacher Value-Added in Prior Year	-0.000		-0.002	
	(0.001)		(0.004)	
Principal Value Added Two Years Prior	0.282	***	0.051	
	(0.073)		(0.371)	
N (Observations)	488		521	
Teachers with Same Principal in Year t and t-1				
All Teachers				
Teacher Value-Added in Prior Year	0.000		0.001	**
	(0.000)		(0.000)	
Principal Value Added	0.347	***	-0.150	
	(0.050)		(0.211)	
N (Observations)	1698		1806	
New Teachers (3yrs or less exp)				
Teacher Value-Added in Prior Year	-0.002		0.003	
	(0.002)		(0.002)	
Principal Value Added	0.281	***	0.019	
	(0.076)		(0.372)	
N (Observations)	469		502	

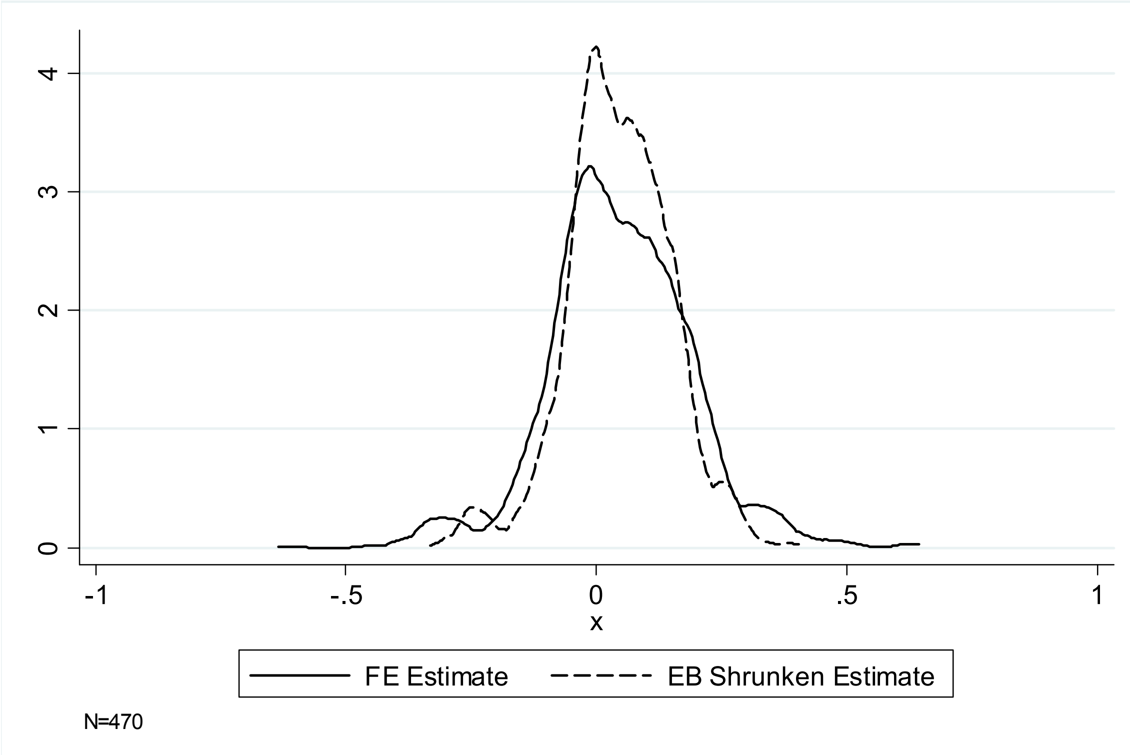
Standard errors are clustered at the teacher level. Outcome is teacher value-added in the current year. Models also control for school year and the lag of teacher experience which is entered as dummy variables and top coded at 20 years. Principal value-added is measured as the average of all years prior to t-1.

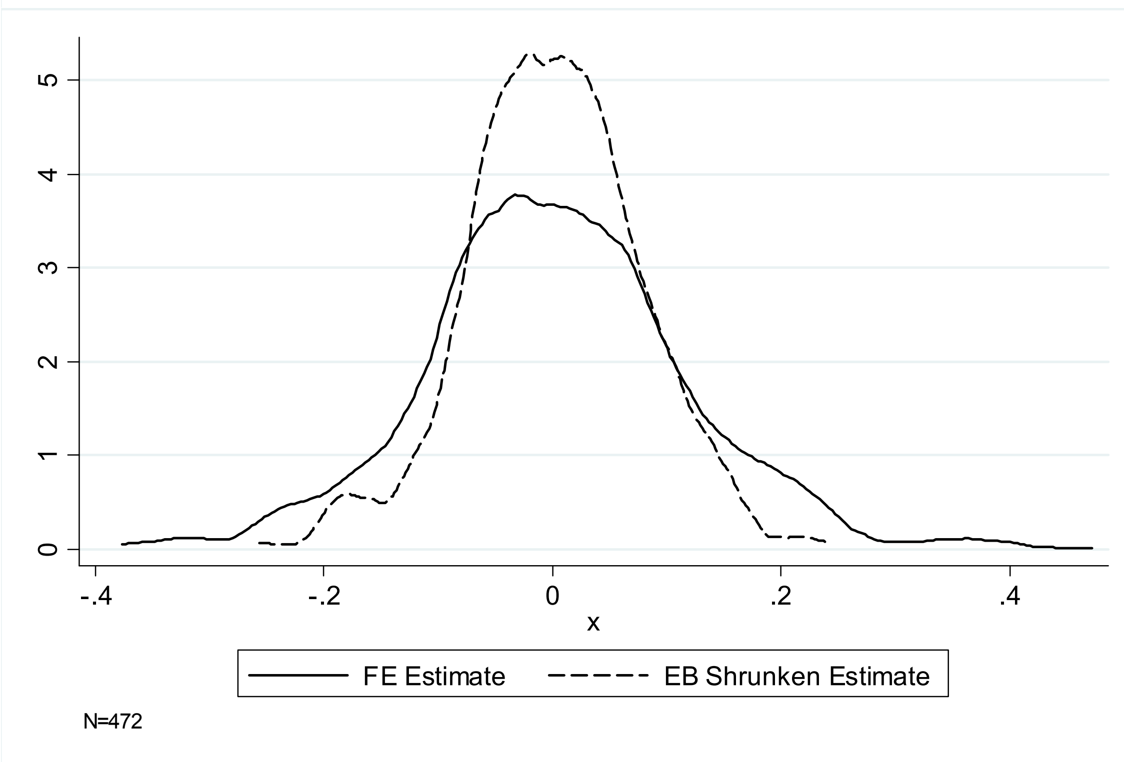
Appendix 1. Model Specifications for Estimating Principal Value-Added
(Shaded columns indicate specifications discussed in the paper.)

	Principal FE			***Principal*Year FE***		
	1	2	**3**	4	5	**6**
Dependent Variable						
Current Score, Control for Lag	X	X		X	X	
Gains: Current Score Less Lag Score			**X**			**X**
Student						
Lagged Test	X	X		X	X	
Student time invariant controls	X	X		X	X	
Student time varying controls	X	X	**X**	X	X	**X**
Student Fixed Effects			**X**			**X**
Principals						
Principal Experience	X	X	**X**			
Teachers						
Teacher Experience	X	X	**X**	X	X	**X**
School						
School Fixed Effects		X			X	
School Controls	X		**X**	X		**X**
Other						
Year FE	X	X	**X**			
Grade FE	X	X	**X**	X	X	**X**
Classroom controls	X	X	**X**	X	X	**X**

Note: Student time invariant controls are race and gender; student time-varying controls are free/reduced lunch eligibility, limited English proficiency, and whether the current grade is being repeated.
School time-varying controls are percent free or reduced price lunch eligibility, percent black, percent Hispanic, and average school achievement score in the prior year. Classroom controls are classroom percent from minority groups, percent female, percent limited English proficient, and average achievement score in the prior year. Principal experience is top coded at 10 years or more and entered as dummy variables.

Appendix Figure 1: Distribution of School Value-Added During Each Principal's Tenure (Principal Effectiveness), using the Student Fixed Effect Specification. Math and Reading





APPENDIX 2: Bayesian Shrinkage

Our estimated principal effect $\left(\hat{\delta}_j\right)$ is the sum of a "true" principal effect $(\delta_{\downarrow} j)$ plus some measurement error[7]:

$$\hat{\delta}\, j = \delta\, j + \varepsilon\, j \tag{2}$$

The empirical Bayes estimate of a principal's effect is a weighted average of their estimated fixed effect and the average fixed effect in the population where the weight, λ_j, is a function of the precision of each principal's fixed effect and therefore varies by j. 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, 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 precision of the estimate. This more efficient estimator of principal quality is generated by:

$$E\left(\delta_{\downarrow}(j)\right) \mid \hat{\delta}_{\downarrow}\, j\big) = \left(1 - \lambda_{\downarrow}(j)\right)\left(\bar{\delta}\right) + \left(\lambda_{\downarrow}\, j\right) * \hat{\delta}_{\downarrow}\, j \tag{3}$$

where $$\lambda_j = \frac{(\sigma_\delta)^2}{[(\sigma)]_{\varepsilon j}\,)^2[+(\sigma)]_\delta)^2} \tag{4}$$

Thus, the term λ_j can be interpreted as the proportion of total variation in the principal effects that is attributable to true differences between principals. The terms in (4) are unknown so are estimated with sample analogs.

$$[(\hat{\sigma})]_{\varepsilon j}\,)^2 = var\,(\hat{\delta}_{\varepsilon j}) \tag{5}$$

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

$$[(\sigma)]_\delta)^2 = [(\hat{\sigma})]_\delta)^2 - mean(\hat{\sigma}_\varepsilon)^2 \tag{6}$$

where $[(\hat{\sigma})]_\delta)^2$ is the variance of the estimated principal fixed effects (Gordon et al. 2006, Jacob and Lefgren 2005). The shrunken fixed effects turn out to be very similar to our estimated fixed effects and correlate at about .96. Since there is only one principal per school, the principal fixed effects are estimated fairly precisely. The shrinking is much more important in the case of teachers who tend to have substantial variation in class size and in the number of students tested which generates more variation in the precision of the teacher fixed effects.

[7] Here we make the classical errors in variables (CEV) assumption, assuming that measurement error is not associated with an unobserved explanatory variable.

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