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Portability of Teacher Effectiveness Across School Settings

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Abstract

Redistributing highly effective teachers from low- to high-need schools is an education policy tool that is at the center of several major current policy initiatives. The underlying assumption is that teacher productivity is portable across different schools settings. Using elementary and secondary school data from North Carolina and Florida, this paper investigates the validity of this assumption. Among teachers who switched between schools with substantially different poverty levels or academic performance levels, we find no change in those teachers' measured effectiveness before and after a school change. This pattern holds regardless of the direction of the school change. We also find that high-performing teachers' value-added dropped and low-performing teachers' value-added gained in the post-move years, primarily as a result of regression to the within-teacher mean and unrelated to school setting changes. Despite such shrinkages, high-performing teachers in the pre-move years still outperformed low-performing teachers after moving to schools with different settings.

1. Introduction

Redistributing effective teachers from low to high-need schools is a key element in a number of current high-profile education policy initiatives. Some of the prominent examples include the Intensive Partnerships for Effective Teaching program supported by the Gates and Melinda Foundation and the Talent Transfer Initiative as well as the Teacher Incentive Fund program, both sponsored by the U.S. Department of Education. Through various mechanisms, these programs seek to make sure that the highest need students are taught by the most effective teachers by transforming how teachers are selected, retained and developed.

The underlying assumption of the focus on teacher effectiveness redistribution is that highly effective teachers sorted by various mechanisms to schools primarily serving students from advantaged backgrounds will perform at a similar high level in high-need school settings. In other words, teacher productivity is portable. However, how teacher performance may be influenced by the changed dynamics between teachers and their new students, colleagues and the overall school environment after they move to a very different type of school is unclear. The goal of this paper, therefore, is to investigate the validity of the teacher effectiveness portability assumption.

The emphasis on redistributing effective teachers as a means of improving student academic performance and closing performance gaps is understandable. Research has consistently shown that teachers are the most important school factor affecting student achievement (Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004; Asronson, Barrow, & Sander, 2007). Having a teacher from the top quartile of the effectiveness distribution is associated with four to six months' gain in student learning as compared with having a teacher from the bottom quartile (Hahnel & Jackson, 2012). Previous studies find that teachers tend to move to and stay in schools with fewer students who are poor, minority or low-achieving from schools with more students who are low-income, non-white or low-performing (Lankford, Loeb, & Wyckoff, 2002; Boyd, Lankford, Loeb, & Syckoff, 2005; Feng, 2009; Clotfelter, Ladd, & Vigdor, 2005). Many high-need schools also have difficulties in hiring effective new teachers at the outset. The challenges that high-need schools face in both hiring and retaining teachers result in inequitable distribution of effective teachers.

Earlier studies find that teachers in high-needs schools tend to have lower *qualifications* than teachers in schools with more advantaged students (Clotfelter, Ladd, & Vigdor, 2005; Lankford, Loeb, & Wyckoff, 2002). However, teacher qualifications, such as educational attainment and certification status, are only weakly correlated with teacher performance and student achievement (Harris & Sass, 2007; Clotfelter, Ladd, & Vigdor, 2007). Years of experience are only related with teacher effectiveness in the first three to five years of teaching and then significantly diminish in the years beyond.

More recent studies, measuring teacher quality by teacher effectiveness associated with student learning, provide a more nuanced picture of teacher quality distribution and teacher mobility. These studies generally use teacher value-added as a measure of teacher effectiveness. In terms of the distribution of effective teachers across schools, Sass, Hannaway, Xu, Figlio and Feng (2011) find small differences in *mean* teacher performance between low- and high-poverty schools. However, the variation in teacher performance is significantly larger in high-poverty schools than in low-poverty schools. Even though high-performing teachers in both school types are equally effective, the least effective teachers in high-poverty schools perform at a much lower level than the least effective teachers in low-poverty schools. Evidence further suggests that the teacher effectiveness differential at the lower end of the value-added distributions is not driven by differences in the performance or the proportion of inexperienced teachers in those two school types.

In terms of teacher mobility, Hanushek et al. (2005) finds that teachers who remain in their schools are on average at least as good as those who exit, in terms of teacher value-added to student learning. In a more recent study, Feng and Sass (2011) look beyond averages and report that teachers at the extremes of the teacher effectiveness distribution are more likely to leave their schools. While addressing the question “who moves”, the literature also provides some evidence on the question “to where”. Among early career teachers in North Carolina public schools, more-effective teachers are not found to be more likely to leave challenging schools than other teachers (Goldhaber, Gross, & Player, 2007). On the other hand, Feng and Sass (2011), using Florida data, report the most effective teachers are more likely to move to schools that already have the highest average teacher quality.

In short, it does appear that the distribution of effective teachers varies by school characteristics. Two recent simulation studies, using New York and Washington data respectively, demonstrate significant student learning gains if schools were to lay off their worst-performing teachers (Boyd D. J., Lankford, Loeb, & Wyckoff, 2010; Goldhaber & Theobald, 2010). These studies suggest that moving effective teachers to disadvantaged schools could potentially raise student performance in those schools. Such conclusions, however, rely on the assumption that teachers will retain their effectiveness in different school settings.

There are a number of reasons why this assumption may not hold. First, students with varying backgrounds and characteristics face different challenges in learning. Teaching methods that have been successful with one type of students may not match the learning needs of other types of students. For example, Xu, Hannaway and Taylor (2011) demonstrate that Teach for America teachers are much more effective working with high-achieving students than with lowest-achieving students.

Second, teacher performance may be affected by school culture, environment and working conditions (Campbell, Kyriakides, Muijs, & Robinson, 2003). Several studies theorize or suggest that school workplace conditions can affect teacher learning (Jacqueline, 2000) and can either encourage or constrain effective teaching practices (Bryk & Schneider, 2002; McLaughlin & Talbert, 2001; Rosenholtz, 1989). In addition, principal behaviors can foster school cultures that promote teacher satisfaction and commitment (Anderman, 1991), and teachers satisfaction is in turn positively related to the instructional support provided by teachers to low-achieving students (Opdenakker & van Damme, 2006). Researchers have also linked teacher "burnout" to organizational factors, such as work pressure from administrators, a lack of trust in teachers' abilities, and disagreeable physical environments (Friedman, 1993; Dorman, 2003). Finally, Jackson and Bruegmann (2009) find strong evidence of teacher peer learning, observing that a teacher's effectiveness is more likely to increase when she has more effective colleagues.

The goal of this paper is to explore whether teacher effectiveness is "portable" across school settings. We determine individual teachers' effectiveness in a value-added framework. We then examine teachers who changed school settings and compare the effectiveness of those teachers before and after the setting change. We define school settings along two dimensions: school poverty rate and school academic performance. Among teachers who switched schools, we find that their post-move performance was not adversely associated with a school move, regardless of how different school settings were between the sending and receiving schools. We find high-performing teachers in the pre-move period tended to have lower value-added in the post-move period, whereas low-performing teachers in the pre-move period tended to have higher value-added in the post-move period. We demonstrate that such a pattern is most likely to be driven by regression to the mean and that it is not associated with school switches. In what follows, we describe the data used in the analysis. Section 3 details the methodology, Section 4 presents the findings and Section 5 concludes.

2. Data and Samples

We use longitudinal student and teacher data from North Carolina (1998-99 through 2008-09) and Florida (2002-03 through 2008-09). In North Carolina, at the elementary level, we focus on 4^{th} and 5^{th} grade math and reading teachers in self-contained classrooms. End-of-grade (EOG) tests in math and reading are administered annually to elementary school students starting from the 3^{rd} grade. This allows us to estimate value-added for teachers in grades 4 and 5, using previous year's student test scores to control for student prior performance. At the secondary level, we focus on Algebra I and English I teachers. End-of-course (EOC) tests are required for both subjects and are typically taken in grade 9 (or earlier in the case of algebra I). Students taking "Algebra I", "Algebra I-B" or "Integrated Math II" are required to take the EOC algebra I test, and students taking "English I" are required to take the EOC English I test. Student EOG math test scores from the previous year are used as pretest scores for Algebra I. Student EOG reading scores from the previous year are used as pretest scores for English I.

Because NC data do not contain direct instructor-student link prior to 2006-07, for those earlier years we use a set of rules to verify whether test proctors (who are linked to individual students) were indeed instructors. This strategy has been used successfully by a number of earlier studies. Specifically, information on students and teachers is contained in two separate files in North Carolina. The instructional classes file is a *classroom level* file that includes aggregate student characteristics and instructor IDs. The test score file is a *student level* file that includes test proctor IDs as well as student test scores and student characteristics. As a result, instructors are not linked directly to individual students; only proctors are. Our task is to verify if proctors are indeed instructional teachers. This verification is done by comparing student characteristics (percent male, percent white, and class size) in the instructional classrooms and those in the test classrooms. To do this we need to 1) aggregate individuals in the test score file into test classrooms and 2) link the test and instructional classes (now both are classroom-level files) by LEA (district), school ID and teacher ID. If the two sets of student characteristics are sufficiently similar (defined as the mean squared difference of the three classroom characteristics), we conclude that test proctors are indeed instructional teachers.

In Florida, we focus on math and reading teachers in the 4th, 5th, 9th and 10th grade. Students in all grades take end-of-grade tests every year. To attribute student learning gains to teachers more accurately, we do the following: 1) Define core math and reading courses. We define core courses in a given subject as those that more than 50 percent of students in a given grade took at a given school. 2) Exclude students with more than one teacher in a given subject.

In North Carolina, we identify about 42,000 unique elementary school math and reading teachers, 10,000 algebra I teachers and 8,000 English I teachers. Among those, 32,000 elementary school teachers, 7,000 algebra I teachers and 6,000 English I teachers can be reliably linked to students. In Florida, we identify about 36,000 unique elementary school math and reading teachers and about 13,000 unique secondary school math and reading teachers. We further restrict our sample by 1) removing charter school teachers 2) removing students and teachers who changed schools during a school year (about 2-4 percent of observations), 3) keeping classrooms (in the analytic sample) with 10 to 40 students, and 4) removing classrooms with more than 50 percent special education students. Our final analytic samples include 21,000 elementary school teachers, 5,000 algebra I teachers and 3,800 English I teachers in North Carolina and almost 30,000 elementary school teachers and 10,000 secondary school teachers in Florida (table 1).

3. Methodology

We approach our research question using a two-stage strategy. At the first stage we estimate teacher annual performance in a value-added framework. Since the purpose of this paper is to compare teacher effectiveness under different school settings, our teacher value-added scores are estimated without controlling for school fixed-effects as many teacher value-added studies do. The resulting teacher value-added estimates therefore consist of a component that is attributable to school effectiveness, a teacher component that represents teacher effects that persist over time, a transitory teacher component that represents teacher-school specific effectiveness and an idiosyncratic component that represents random year-to-year teacher performance fluctuations as well as fluctuations that may be driven by unobserved time-varying school, classroom and student characteristics.

At the second stage we explore how estimated teacher value-added changed over time among teachers ("setting changers") who moved to schools with substantially different school environment from the sending schools. The pre-to post-move change in teacher value-added is then compared to the changes among teachers who switched to schools with environments similar to the sending school. The following sections will discuss value-added estimation, difference-in-differences analysis and school setting definition in details.

3.1 Estimating teacher quality by value-added

The usual value added model begins with the assumption that education is a cumulative process: student achievement is a function of inputs to the education process in the current year as well as in all preceding years. Focusing on teachers, this is to say that a student *i*'s achievement in year *t* is a function of his/her teacher in that year and in all previous school years (and any other relevant inputs). Under the assumptions that a) the marginal effect of a teacher on a student's achievement in the contemporaneous year is constant across years and that the relationship between teacher inputs and student achievement is linear, and b) student knowledge decays from one year to the next at a constant rate, the relationship between teachers and student achievement can be presented in the following form:

$$A_{it} = T_{it}\beta + \alpha T_{it-1}\beta_{t-1} + \alpha^2 T_{it-2}\beta_{t-2} + \alpha^3 T_{it-3}\beta_{t-3} + \cdots + \varepsilon_{it}$$
$$= T_{it}\beta + \alpha(T_{it-1}\beta_{t-1} + \alpha T_{it-2}\beta_{t-2} + \alpha^2 T_{it-3}\beta_{t-3} + \cdots) + \varepsilon_{it}$$

where A_{it} measures student *i*'s achievement in year t, T_{it} is a vector of indicators measuring student *i*'s teacher assignment in year t, β's are vectors of coefficients measuring the effect of individual teachers conditional on all other included variables, α measures the rate at which student achievement gains persist and ε_{it} is a random error. It is easy to see that the terms in parentheses simply represent A_{it-1}, the lagged student achievement. Therefore, the above model can be simplified and rewritten as:

$$A_{it} = T_{it}\beta + \alpha A_{it-1} + \varepsilon_{it}$$

The parameter of interest is the effect of current teacher on current student achievement, given by the vector of teacher-specific effects β, after controlling for the cumulative contribution to student learning of teachers in previous years as captured by the lagged achievement term. Models of this form are typically referred to as value-added models. A variant of the above model, which uses achievement level as its dependent variable, is an achievement gains model of the following form:

$$A_{it} - A_{it-1} = T_{it}\beta + \varepsilon_{it}$$

Both the gains and levels models are commonly used in the empirical literature on value-added measures of teacher effectiveness. The levels model is flexible in that it does not impose a specific assumption about the rate at which knowledge decays over time; instead it allows that rate α to be estimated.

However, since student achievement is likely to be serially correlated, the inclusion of the lagged achievement term on the right hand side of the levels model leads to correlation between the regressor and the error term; consistent estimation requires instrumental variables methods as described by Anderson and Hsiao (1981, 1982), Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), and Blundell, Bond, and Windmeijer (2000). Furthermore, measurement error in the lagged achievement term introduces downward bias in the estimate of the persistence rate α and may also induce bias in other coefficients (including teacher effects) if teacher assignments are conditioned on observed test scores and information available to school staff but not in the administrative data.

The gains model, on the other hand, solves these two statistical problems by removing the lagged achievement term from the list of regressors. But in doing so, the gains model imposes the restriction of zero decay of knowledge. That is, the effect of a student's teachers in all preceding years carries forward to the current time period unabated.

There is only imperfect evidence on the relative importance of decay, often in the form of "fade out" of estimated effects over time, observed in most educational interventions, and estimated coefficients less than one when estimating the levels model described above. However, if one estimates the levels model above instrumenting for lagged achievement using twice-lagged achievement following Anderson and Hsiao (1981, 1982), the estimated coefficient on lagged achievement is approximately one (from 0.98 to 1.0 in our estimated models) compared to estimates between 0.5 and 0.7 without instrumenting. This is strong evidence of the downward bias due to white noise measurement error in lagged achievement, which may induce bias in other coefficients. This is consistent with conclusions drawn in Hanushek (1992) that test measurement errors are important in biasing the estimates of educational production functions that include lagged test scores on the right hand side. Given these findings, the gains model is our preferred model in this paper and will be the focus of discussion. The levels model is nevertheless still estimated to examine if key findings are robust across various model specifications.

Value-added models assume that lagged student achievement sufficiently captures all historical inputs and heritable endowments in the education process (Todd & Wolpin, 2003), thus separating the current teacher's contribution to student learning from the effects of teachers and other education inputs in earlier years. However, students and teachers are not randomly sorted into schools, and teachers are typically not randomly assigned to classrooms. To mitigate a variety of selection issues, our empirical models control for observable student characteristics is:[1]

$$A_{it} - A_{it-1} = T_{it}\beta + X_{it}\gamma + \varepsilon_{it}$$

where A_{it} is student test score normalized by year, grade and subject so that it has a mean of 0 and standard deviation of 1.[2] Student characteristics variables, X_{it}, include 1) whether or not a student repeated a grade in year *t*, 2) his free/reduced price lunch eligibility, 3) sex, 4) race/ethnicity, 5) whether or not he is classified as gifted, 6) special education status by type of disability (speech/language disability, learning disability, cognitive/mental disability, physical disability, emotional disability and other types of disability), 7) school mobility and 8) grade level. We differentiate two types of school mobility: structural school change and non-structural school change. Structural school change is defined as when at least 30% of student *i*'s classmates from the previous school moved to the same receiving school in the current year. Otherwise a student school change is defined as non-structural.

Bias

Because teachers in our analytic sample are linked to a single classroom each year in most cases, our models cannot accommodate classroom characteristics variables. In addition, as the primary purpose of this study is to compare teacher value-added in different schools and school settings, our models do not include school fixed effects. The inclusion of school fixed effects would leave us with within-school variation in teacher value-added estimates and preclude any cross-school comparisons.

Without controlling for school fixed-effects, one might be concerned with attributing all school effects, such as the effectiveness of school leadership, to teachers. Previous literature on value-added modeling demonstrates that most of the variation in estimated teacher value-added is among teachers working in the same school rather than differences across schools (Kane & Staiger, 2008). Our estimates clearly support this view: in

[1] We also estimate a levels model in which we control for the same set of student characteristics variables as well as lagged test scores in the same subject, its quadratic term, and lagged test scores in the opposite subject.

[2] One concern with the gains model is the observation that score gains are higher for students who start at a lower initial performance level. This correlation could be the result of regression to the mean; it could also result from the properties of state-designed standardized tests, which may have more differentiation power at the lower end of the student ability distribution. The effectiveness estimate of teachers in high-performing classrooms and schools, as reflected on state standardized tests, could be penalized as a result. To address this concern, we follow a strategy employed by Hanushek, et al (2005) and estimate an alternative gains model in which we divide students into deciles according to their lagged test scores and then standardize score gains within each lagged score decile.

our teacher samples, between-school variation accounts roughly for 12-20 percent of the total variation in estimated teacher value-added each year. Earlier studies find that the inclusion of school fixed-effects in value-added models affects teacher value-added estimates only marginally. Kane and Staiger (2008) report the standard deviation of math teachers' value-added estimates change from 0.23 s.d. to 0.22 s.d. when school fixed-effects are added to the model and from 0.18 s.d. to 0.17 s.d. for English language arts teachers. More recently, Chetty, Friedman and Rockoff (2011) demonstrate that models without school fixed-effects produce teacher value-added estimates that are highly predictive of student test scores in years that are not used in estimating teacher value-added. Using a quasi-experimental design, Chetty, Friedman and Rockoff (2011) also conclude that bias in estimated teacher value-added due to sorting/selection on unobservables is negligible, a finding consistent with that reported by Kane and Staiger (2008) who use an experimental design.

Although the literature on teacher value-added is frequently concerned with school effects as a confounding factor in the estimation of teacher value added, schools may also influence teacher value-added estimates by bringing about meaningful changes in teachers' true productivity. The first type of school influence on teacher value-added estimates leads to potential bias in those estimates, misattributing school effects to individual teachers, whereas the second type of influence does not "bias" the estimates. Consider this in a production function framework; it is entirely understandable that the productivity of an input (a teacher) will vary by the level of available production technology (e.g. school safety, effective leadership). A couple of recent studies appear to support this view empirically. Jackson (2010) reports within-teacher variation in value-added that is between schools to be substantial, indicating that schools can boost or depress a teacher's performance depending on the "match quality" between schools and teachers. Jackson and Bruegmann (2009) also find that a teacher's productivity increases when she has more effective colleagues, probably one of the mechanisms through which a school can make a teacher better or worse. As a result, in the second stage analysis where we investigate how teacher value-added changes in relation to school switches, we control for classroom characteristics and a measure of school quality that is based on the average peer value-added among teachers in the same school. We assess how much the relationship between teacher value-added and school switch changes with and without classroom and school/peer quality controls.

Noise

In all our empirical models we estimate teacher value-added by year. A number of studies show that value-added estimates of teacher effectiveness are unstable from year to year (e.g., Koedel & Betts, 2007; McCaffrey, et al., 2009). Instability of value-added measures may indicate substantial amount of noise in these teacher effect estimates, variation in true performance, or both. Random fluctuations due to noise may be reduced with more student observations per teacher, and therefore we restrict our analytic samples to classrooms with at least 10 students. In addition, we implement an Empirical Bayes (EB) or "shrinkage" estimator (Gordon, Kane & Staiger, 2006; Kane, Rockoff & Staiger, 2006). The procedure acts to shrink teacher effects for cases with fewer student observations toward the average teacher effect, with the amount of shrinkage proportional to how much of the total variation in teacher effects appears to arise from noise. The total variation in teacher effects is the variance in teacher effects across teachers. We then estimate the "signal" (persistent teacher effects) by taking the difference between the variance in teacher effects across teachers and the variance of individual teacher effects (i.e., the "noise"). We then compute the signal-to-noise ratio for each teacher, a measure of the reliability of our teacher effect estimates, and use it to compute shrinkage factors in the EB estimates (giving less weight to less reliable estimates). Specifically, the estimated teacher effects $\hat{\beta}$ consist of true teacher effect β and random errors τ:

$$\hat{\beta} = \beta + \tau$$

The total variation in the estimated effects on student performance by teacher ($\hat{\sigma}_{\beta}^2 + \hat{\sigma}_{\tau}^2$) includes estimation error and other sources of non-persistent variation in test performance ($\hat{\sigma}_{\tau}^2$), in addition to persistent differences in performance between teachers ($\hat{\sigma}_{\beta}^2$). The reliability of the teacher effect estimate is given by:

$$\hat{\lambda} = \frac{\hat{\sigma}_{\beta}^2}{\hat{\sigma}_{\beta}^2 + \hat{\sigma}_{\tau}^2}$$

The shrunken teacher value-added estimates, $\tilde{\beta}$ is then:

$$\tilde{\beta} = \bar{\hat{\beta}} + \hat{\lambda}(\hat{\beta} - \bar{\hat{\beta}})$$

where $\bar{\hat{\beta}}$ is the average estimated teacher effect across all teachers or subgroups of teachers.

3.2 Difference-in-differences analysis

We use a difference-in-differences strategy to describe how a teacher's value-added may shift following a school setting change. Teachers are divided into three groups: Those who did not switch schools, those who switched between schools with similar settings in terms of school performance or school poverty level, and those who switched between schools that have substantially different settings. We model how teacher annual value-added estimates vary with experience among all teachers, and estimate how a school switch may disrupt the average teacher productivity-experience profile. We compare the two groups of school switchers, differencing the pre-post teacher value-added differentials in those two groups. By doing so, we take out the possible impact of school change on teacher value-added that is common to all teachers who changed schools, thereby estimating whether moving to a substantially different school setting is associated with additional changes in a teacher's productivity above and beyond the average relationship between a school change and teacher productivity.

With this strategy, we take a school change, sometimes moving between schools with very different environments, as given. In other words, this analysis is not trying to estimate the causal impact of school moves on teacher productivity; rather, we describe pre- to post-move teacher productivity differences conditional on a teacher changing schools. We estimate the following regression equation:

$$\hat{\beta}_{jt} = Y_t + T_j + X_{jt}v_1 + S_jv_2 + C_{jt}v_3 + Post_{jt}v_4 + Post_{jt}DP_jv_5 + Post_{jt}DN_jv_6 + \varepsilon_{jt}$$

where $\hat{\beta}_{jt}$ is the estimated value-added for teacher *j* in year *t*. As $\hat{\beta}_{jt}$ is estimated with error, we implement an FGLS estimator to take into account standard errors associated with $\hat{\beta}_{jt}$. Y_t is a vector of year indicator variables and T_j is a vector of teacher indicator variables. X_{jt} is a set of teacher experience variables (3-5 years, 6-12 years and 13 or more years, with 0-2 years as the reference group). With teacher fixed-effects and teacher experience variables, our model compares a teacher with herself in the years before and after a school switch, based on her value-added that is independent from experience.

Part of the year-to-year variation in $\hat{\beta}_{jt}$ reflects variation in school effects and classroom assignments. In the difference-in-differences model we control for both. S_j is a measure of school quality, calculated as the average value-added of a teacher's peers in the same school. Past research has shown that a teacher's peers play a significant role in her productivity (Jackson and Bruegmann, 2009; Jackson 2012). Moreover, the quality of a teacher's peers may also reflect effectiveness of school leadership to the extent that it reflects a school's ability in attracting and retaining good teachers or in supporting teachers' work effectively. C_{jt} is a set of classroom characteristics variables: percent of students eligible for free/reduced price lunch, average pretest scores, and the standard deviation of pretest scores. The standard deviation of pretest scores is included with the hypothesis that a classroom with more uniform starting levels is probably easier to teach than a classroom that is more heterogeneous.

$Post_{jt}$ is an indicator variable for the post-move years.[3] Its coefficient, v_4, captures the difference between a teacher's average post-move value-added and her *own* average pre-move value-added. It is interacted with DP_j and DN_j, two indicator variables that capture how the settings of the receiving school differ from those of the sending school. Specifically, DP_j=1 (0 otherwise) if the school setting measure of the receiving school is substantially higher than that of the sending school, and DN_j=1 (0 otherwise) if the school setting measure changes in the opposite direction.

School setting is defined along two dimensions: school performance and school poverty. We estimate the regression equation separately for these two dimensions. We start with continuous measures of school performance and poverty. In North Carolina, schools report their percentages of students who performed at or above grade levels each year. We standardize this measure by year and aggregate it across all years during the study period to characterize a school's performance level. North Carolina also reports school performance in terms of growth. Ideally we would like to describe a school's performance "setting" in terms of both levels and growth. However, we do not have access to a continuous measure of school growth that form the school growth

[3] Alternatively, we flag each pre-school change and post-school change years separately to allow for more flexibility. We center all years around the year of move, so that pre-move years are represented by a series of dummy variables I_{t-1}, I_{t-2}, I_{t-3}… and post-move years are represented by I_{t+1}, I_{t+2}, I_{t+3}, …. Our findings are not affected by this alternative specification. Coefficients on the pre-move year dummies are not significantly different from one another, and neither are coefficients on the post-move year dummies. Results are available upon request.

categories reported in our data set. In the Florida data, by contrast, we have access to school performance scores that combine levels and growth, scores that have been used to assign grades to schools in the state. Like in North Carolina, we first standardize these scores by year and aggregated them over time. When a teacher switches schools, we calculate the difference between the sending and receiving schools' performance scores. The second column in Figure 1 shows the distribution of school performance difference between the sending and receiving schools. One standard deviation of school performance differentials is about 0.97 standard deviations in school performance scores in Florida and 0.76 standard deviations in North Carolina.

Sending and receiving schools are defined as similar in school performance setting if their performance score difference is within +/-0.25 standard deviations. These school moves serve as our reference group. If the receiving school has a performance score that is 0.25 standard deviations *higher* than the sending school, DP_j=1, indicating that a teacher moved to a higher-performing school. If the receiving school has a performance score that is 0.25 standard deviations *lower* than the sending school, DN_j=1, indicating that a teacher moved to a lower-performing school.

We measure a school's poverty setting using the percentage of free/reduced price lunch eligible students. For each teacher, we aggregate the reported school FRPL percentages across all the years in which the teacher taught in that school. When a teacher switches schools, we calculate the difference in average FRPL percentages in the sending and receiving schools. The first column in Figure 1 shows the distribution of school poverty difference between the sending and receiving schools. One standard deviation of school poverty differentials is about 28 percentage points in school FRPL poverty level in Florida and 25 percentage points in North Carolina. Sending and receiving schools are considered similar in school poverty setting if their FRPL percentage difference is within +/-15 percentage points. DP_j=1 if the poverty rate of the receiving school is 15 or more percentage points *higher* than that of the sending school, and DN_j=1 if the poverty rate of the receiving school is 15 or more percentage points *lower* than that of the sending school.

Coefficient v_4 captures the within-teacher value-added difference between her pre- and post-move years if her sending and receiving schools are similar in academic performance or poverty. Coefficients in vector v_5

estimate whether moving to a substantially different school setting is associated with additional pre-post value-added difference. The hypothesis is that teacher productivity may be affected by the larger demand on teachers who move across schools that are more different.

A Difference-in-differences design gives rise to two potential sources of correlation among observations, the “clustering problem” (multiple observations within each teacher) and the “autocorrelation problem” (serial correlation over time) (Hansen, 2007). Both clustering and positive autocorrelation will lead to underestimation of standard errors. The severity of this problem depends on the length of the time series used, the serial correlation of the dependent variable, and the serial correlation of the independent variables. Although having fewer time periods and having higher serial correlation in the dependent variable diminish the problem of standard error underestimation (Bertrand, Duflo, & Mullainathan, 2004), serial correlation in the independent variable will exacerbate the problem. Since the main independent variables of interest, the school move indicator and move type indicators, change only once during the study period and remain the same within either the pre-move or the post-move periods, they are highly correlated from year to year. As a result, serial correlation has especially large effect on standard errors in difference-in-differences models (Bertrand, Duflo, & Mullainathan, 2004; Kezdi, 2004).[4] In the analyses that follow, we estimate robust standard errors that are clustered by teacher (the “Huber-White standard error”). We shall keep in mind, however, that these standard errors may be subject to small sample bias (e.g. N=10), as demonstrated in Bell and McCaffrey (2002).[5]

4. Findings

4.1 Descriptive summary

Among all teachers in our study samples, about 11 to 13 percent of teachers in both states switched schools once during our study period. Secondary school reading teachers in both states had lower mobility rates,

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[4] Bertrand, Duflo and Mullainathan (2004) show 45 to 65 percent rejection rates of a t-test on a placebo binary treatment that should have a correct nominal rejection rate of 5 percent based on simulation results.

[5] Although the clustering problem has long been recognized in the econometric literature on panel data analysis, the serial correlation problem has started receiving more attention only relatively recently. A number of techniques have been proposed but none provides a perfect solution (Bertrand, Duflo, & Mullainathan, 2004; Hansen, 2007; Kezdi, 2003). These papers demonstrate that a generalized “cluster” estimator to compute the standard errors (White, 1984; Arellano, 1987) has some of the most desirable properties.

at just below 10 percent. Not all teachers are observed for all the years. Table 2 shows that around 30 percent of all elementary school teachers in both states, just under 20 percent of North Carolina secondary school teachers, and about 23-32 percent of Florida secondary school teachers were observed for four or more years at the elementary school level. Teachers who switched schools tended to be observed in our analytic sample for longer periods of time. In most cases around 50-60 percent of school switchers were observed for four or more years.

Table 2 also shows the number of school switchers by school setting differences between the sending and receiving schools. Among elementary school teachers who switched schools, about 70 percent in North Carolina and 78 percent in Florida moved to a school with substantially higher or lower performance level than the sending school. Around 55 percent of school switchers in both states moved to a school with substantially different school poverty rate. At the secondary level, about 78 to 82 percent of school switchers in both states moved to a school with different school performance level. By contrast, most secondary school switchers in both states moved to schools with similar school poverty rates (65 percent in North Carolina and 60% in Florida).

In both states, when teachers moved to schools with different settings, they were more likely to move to a more advantaged school setting (higher performance level or lower poverty level) than to a less advantaged school setting, not surprising given research on teacher mobility (see, for instance (Goldhaber et al. (2007), and Feng and Sass (2011).

We compare teachers the year before they switched schools with those who stayed in the same school in table 3. Teachers who switched schools were more likely to be inexperienced (0-5 years of experience), and they were less likely to have graduate degrees. In North Carolina where data are available, teachers who switched schools were less likely to be NBPTS certified, with the exception of secondary Algebra I teachers. On average, teacher value-added, regardless of the model specification implemented, among those who switched schools the following year was slightly lower (but statistically insignificant) than that of non-movers. Again, North Carolina Algebra I teachers were an exception: movers' value-added in the year before the move was 0.08-0.10 standard deviations lower than that of non-movers.

4.2 Analytic findings

Tables 4-7 report the estimated teacher value-added change associated with school moves. The first row in each table reports the average pre-post change in teacher value-added across all teachers who switched schools. The other rows in each table report how teacher value-added may have changed among those who a) moved from a higher performing/poverty school to a lower performing/poverty school, b) switched between schools with similar performance/poverty levels, and c) moved from a lower performing/poverty school to a higher performing/poverty school.[6] Models II and IV both control for school peer quality and classroom characteristics. Models I and III do not control for school or classroom covariates. They are provided to demonstrate how "move effects" might be affected by school and classroom controls. Not shown in the tables, the coefficients on all school and classroom controls are statistically significant for both math and reading at both the elementary and secondary levels in the two states. We will focus on the results from models II and IV in the discussions below.

At the elementary school level, the average post-move teacher value-added among North Carolina math teachers improved by 0.004 standard deviations as compared with their own average pre-move value-added (table 4). The within-teacher pre-post difference in value-added, however, varied by similarities/differences between the sending and the receiving schools. Teachers switching between schools with comparable performance levels or poverty levels saw no change in their value-added after moving. Neither did teachers who moved to a more advantaged school (higher-performing or lower-poverty). Interestingly, teachers who moved to a more disadvantaged school setting (lower-performing or higher-poverty) increased their value-added in the post-move years (by about 0.020 standard deviations).

We find similar patterns among North Carolina elementary school reading teachers (table 5). On average a school change is associated with 0.005 standard deviation increase in teacher value-added. Although teacher value-added changed insignificantly among those who switched between similar schools and those who moved to

[6] The "effect" reported for teachers moving between similar school settings is the estimated coefficient v_4 in our difference-in-differences regression, whereas those reported for teachers moving from high- to low-settings and from low- to high-settings are the sum of coefficients v_4 and v_5.

a more advantaged school setting, moving to a more disadvantaged school setting is associated with teacher value-added gains.

The Florida elementary school findings are somewhat different (tables 4 and 5). On average, a school move is not associated with any significant change in math teachers' value-added but is associated with significant gains in reading teachers' value-added. More importantly, for both math and reading teachers who moved to a more advantaged school setting (higher-performing or lower-poverty), their value-added improved. No significant change was detected among teachers who switched between similar schools or moved to a less advantaged school setting.

At the secondary school level, with the exception of North Carolina Algebra I teachers, teacher value-added is not associated with school changes, regardless of the similarity/difference between the performance and poverty settings of the sending and receiving schools. On average North Carolina Algebra I teachers gained 0.056 standard deviations in value-added in the years following a school move. Positive gains in value-added were associated with moving to a similar school, moving to a lower-performing school, or moving to a lower-poverty school.

We were concerned with some teachers having only one pre-move year observation or one post-move year observation. Teacher value-added based on a single year of student data, even after requiring at least 10 student observations per classroom and shrunken based on the "signal/noise" ratio, tends to be unstable. Additionally, pre-move performance value-added based on a single pre-move year may be biased as teachers in anticipation of a school change may alter their behavior or effort levels, something similar to the "Ashenfelter dip" (Ashenfelter, 1978). This fact suggests that selection for school changes may be affected by individual-transitory shocks in pre-move teacher performance. On the other hand, in the year immediately following a school change, a teacher's productivity may be affected by the need to adjust to the new environment and therefore may not represent her actual productivity. As a robustness check we re-estimate all the regressions with samples restricted to those teachers with at least two pre-move years and two post-move years. Additionally, we add indicator variables for the last pre-move year and the first post-move year such that our pre-post comparisons are based on years other than those two. Our findings in tables 4-7 remain unchanged and the coefficients on the last pre-move year and the first post-move year are statistically insignificant (with the exception of NC elementary reading, where we see a significant dip in teacher value-added in the last pre-move year (coefficient= -0.017, significant at 1%)).

It is also plausible that teachers who moved across districts and teachers who made within-district moves display different pre-post performance patterns: cross-district movers may have to adjust to more school and district-level differences than within-district movers; The cost of moving to a different district is probably larger than the cost of within-district moves, and so cross-district movers and within-district movers may have different characteristics and motivations to begin with. We test for this possibility by adding a cross-district move indicator to the regression equation and find it consistently not significant across all our analytic samples. [7]

In summary, although our analyses show somewhat different findings between North Carolina and Florida at the elementary school level, it seems that school moves are associated with no change or positive gains in teacher value-added. In both states at both school levels, teachers who switched schools in our data did not appear to suffer from productivity loss no matter how the receiving schools differed from the sending schools in terms of school performance levels or poverty levels.

Education policy makers are not only interested in how teacher effectiveness change before and after a school move, but also (and probably more) interested in whether high-performing teachers retain their effectiveness after moving to a different school with different environment. This is evidenced by a recent report released by the Institute of Education Sciences that implements and examines the effects of a teacher incentive program aimed at inducing high-performing teachers to work in low-achieving schools.[8]

In tables 8-11 we divide teachers into subsamples based on their average pre-move performance levels.[9] In order to measure teachers' pre-move performance level more accurately, in this analysis we limit our sample of teachers to those with at least two years of prior value-added estimates. Teacher value-added is first transformed

[7] We also re-estimated all equations using teacher value-added estimates based on the "levels" models. Again, findings in tables 4-7 remain unchanged. Results are available upon request.
[8] More information about the implementation and preliminary findings can be found at http://ies.ed.gov/ncee/pubs/20124051/.
[9] For non-movers their performance level is based on their average value-added across all years.

into percentiles within each year and then averaged across all pre-move years for each teacher. Teachers whose value-added averaging below the 30th percentile are categorized as low-performers and those averaging above the 70th percentile are categorized as high-performers. We then estimate models II and IV for high-performing, average-performing, and low-performing teachers separately. A clear pattern emerges: Low performers tended to gain in value-added after a school move, and high performers tended to lose in value-added after a school move. No matter whether a teacher moved to a more advantaged school, a similar school, or a less advantaged school, high performers' value-added dropped after the move and low performers' value-added improved after the move.

Given this pattern, the average "move effect" found among all teachers who changed schools could simply be driven by the proportion of movers who were high performers relative to the proportion of lower-performing movers. There is some suggestive evidence for this interpretation. Take elementary school math teachers as an example. In North Carolina, among teachers who moved from a lower-poverty school to a higher-poverty school 61 percent of them were low performers. Since low performers gained about 0.120 standard deviations by moving to a higher-poverty school and high performers lost about 0.063 standard deviations by moving in the same direction, on average movers from lower to higher-poverty schools saw their value-added improve after the move. That is indeed what was reported in table 4. By comparison, about half (48 percent) of teachers moving in the opposite direction (from a higher-poverty to a lower-poverty school) were low performers. Since low performers who moved from higher to lower-poverty schools gained in valued-added an amount comparable in magnitude to that lost by high performers who moved in the same direction (about 0.08 standard deviations), on average there is no significant gain or loss in teacher value-added as associated with moving from a higher poverty school to a lower poverty school.[10]

The strong and consistent pattern found in table 8-11 is probably not surprising. In the pre-move period, teachers are categorized as high and low performers based on their yearly value-added estimates. Yet, these

[10] Earlier research (Jackson, 2010) finds that, based on similar data from North Carolina elementary schools in a different time period, teachers who moved to a different school improved in their value-added. This is consistent with what we have found with more recent data from North Carolina elementary schools. The earlier study proposes a different interpretation based on the "match quality" theory: Movers raised their performance level in the post-move years because they were seeking and generally found a better match between schools and individual teachers.

estimates are measured with error—both measurement error and yearly fluctuations in performance that do not persist over time (McCaffrey, Sass, Lockwood, & Mihaly, 2009). Goldhaber and Hansen (2010) further argue that teacher performance is dynamic over time, with performance that is more highly correlated in adjacent years than over a longer period of time. Both studies argue teacher value-added estimates, even those which aggregate performance over multiple years (like what we did here), bias predictions of future performance towards performance that does not persist over time. In our case, therefore we expect that categorizing teachers into high and low performance groups during the pre-period will overstate the permanent differential in teacher quality across teachers (as our categorizations include performance that does not persist). Hence, we expect that high and low performing teachers will naturally converge to the permanent component of teacher quality during the post-move period (i.e., regression to the within-teacher performance mean).

To find out whether our findings are driven by “regression-to-the-mean”, we create a pseudo move year that is arbitrarily defined as one year before the actual year of move, and examine if similar patterns can be detected before and after the pseudo move year. Figure X visually inspects how teacher value-added changed over time using Florida elementary school math teachers who moved between schools with similar/different poverty settings as an example. On the left we trace how teacher value-added evolved over time around the actual year of move. On the right the same exercise is repeated for time periods around the pseudo move year. In both cases we center all years on the year of move (or the pseudo move year). The top three lines trace how high-performing teachers in the pre-move years changed in their post-move performance. The three lines depict high performing teachers who moved to a school with similar poverty level to that of the sending school, those who moved to a lower-poverty school and those who moved to a higher-poverty school. The bottom three lines mirror the top three lines, and they depict how low-performing teachers in the pre-move years changed in performance over time.

The figure on the left, based on the actual year of move, clearly reflects the pattern found in tables 8-11. The figure on the right, based on the pseudo move year, demonstrates a strikingly similar pattern. High-performing teachers in the arbitrarily-defined “pre-move” years experienced decrease in value-added in “post-move" years and low-performing teachers experienced gains. Such a pattern around the pseudo move year has nothing to do with teachers switching schools since in reality teachers stayed in the same school in the year immediately after the pseudo move year. The difference-in-differences analyses were repeated for high, low and average performers and the relationship between pre-move teacher performance level and post-move performance change around the pseudo move year is reported in tables 12-15.[11] These findings strongly suggest that regression-to-the-mean is the main reason driving the patterns reported in tables 8-11.

It should be noted that since the estimated relationship between teacher value-added and actual school moves do not coincide exactly with pseudo school moves, changing schools may have additional association with changes in teacher value-added estimates that cannot be fully attributed to regression to the mean. Using elementary school teachers, we report adjacent year correlations of teacher value-added estimates in table 16. 95% confidence intervals of these correlations are presented in the parentheses. The correlation coefficients of teacher value-added between the years immediately before and after a school move tend to be lower than the adjacent year correlations in the non-move years. However, the difference is only significant for elementary school math teachers in North Carolina. This indicates, among other possible theories, that some teachers found their new schools to be a better "fit" whereas others may find a worse "fit", thereby lowering the adjacent year correlation around the time of move.

Finally, it is important to point out that despite the "shrinkage" of value-added estimates towards the mean in the post-move years, high-performing teachers were still more effective in their new schools than low-performing teachers were in most cases (table 17). The effectiveness "gap" between high and low-performing teachers was exaggerated in the pre-move years due to measurement errors as well as changes in teacher effectiveness year to year. The gap was narrowed but it persisted in the post-move years, implying that a significant amount of information on teachers' long-term effectiveness was captured by pre-move teacher value-added estimates.

[11] We also experimented with defining the pseudo move year as two years before the actual year of move and found that the patterns persisted.

5. Summary and Discussion

Every year around ten percent of teachers switch schools across the country. This paper estimates how teacher performance, as measured by teacher value-added, is associated with a school move. We are especially interested in whether moving to a school with substantially different settings from those of the sending school is associated with any change in teacher value added. This is an important question, as a number of recent education policy initiatives emphasize the redistribution of teacher quality as a way in improving student academic performance and to close the performance gaps between advantaged and disadvantaged students. For this type of strategy to work, teachers moving from one type of school settings to another need to maintain their level of performance despite any disruptions caused by changing school affiliations. Our findings from North Carolina and Florida, using seven to 11 years of teacher performance data, show that teachers *who moved* did appear to maintain or improve their performance in post-move years. Our models compare teachers with themselves in the pre- and post-move years, accounting for teacher productivity growth associated with experience, teacher peer quality differentials between schools, as well as for variation in classroom characteristics over time. We also find that switching between schools with substantially different school performance levels or school poverty levels does not hurt teacher performance. Regardless of the direction of the move (from more advantaged to less advantaged school setting or vice versa), teacher performance either did not change or improved slightly.

Our analyses cast doubt on the "match quality" theory, which predicts that teachers change schools in order to find a better match between teachers and schools, and therefore teacher performance will improve after a school move as the result of better matching quality. Our empirical estimates (particularly among North Carolina elementary school teachers) appear to be consistent with this theory. Yet our interpretation is different. There is a clear and consistent pattern that teachers who were high performers before a school move tended to have lower value-added in post-move years, whereas the reverse is true for teachers who were low performers in the pre-move period. As a result, the higher average post-move value-added could simply be driven by the higher proportion of movers who were low performers. This is indeed the case among North Carolina elementary school-switchers (60 percent of movers who experienced substantial school setting change were low-performing teachers in the pre-move period).

Our analyses further provide strong suggestive evidence that such patterns (post-move gains for low-performing teachers and post-move loss for high-performing teachers) are driven by regression to the within-teacher mean. Since teacher performance is measured with error and it fluctuates from year to year, classifying teachers into high and low-performing categories based on their pre-move value-added exaggerates their permanent differences in productivity that will persist over time. Therefore, in the post-move period, the performance differential of these two groups of teachers will moderate. We devise a pseudo move year that is set to one year before the actual year of move and find similar post-move gains for low-performing teachers and post-move loss for high-performing teachers, indicating that the observed patterns are not associated with teachers changing schools or school settings.

In summary, we find that among teachers who changed schools there is at least no average loss in teacher performance associated with a school change. This is true even among those teachers who switched school settings. Despite the shrinkage of pre-move teacher value-added estimates in the post-move years, high-performing teachers in the pre-move period still outperformed low-performing teachers in the post-move period. It should be noted that all the estimates are conditional on current policies and practices about filling teacher vacancies that are decided by teacher seniority rights and some degree of principal discretion. Those who move and those who stay differ on observable and unobservable characteristics, and even if we could match movers with non-movers based on the observables, drawing conclusions about the causal effect of a school move on teacher performance would still be tenuous at best. Policy initiatives intended to devise new incentives or mechanisms into an existing education system to encourage teacher quality redistribution may motivate an entirely different group of teachers to switch schools than those who moved under current policies, and therefore findings from this paper should not be over-generalized.

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Tables and Figures

Table 1. Number of teachers in state and sub-samples, by sample restriction steps

	North Carolina		Florida	
	Elementary	Secondary	Elementary	Secondary
math				
Teachers of relevant classes	41,691	10,216	36,446	12,633
Teachers linked to students	32,205	7,153	36,446	12,633
Eliminate charter school classes	22,254	6,330	34,717	12,195
Keep classes with 10-40 students who has no missing values on student and teacher variables	21,119	4,999	29,989	9,101
reading				
Teachers of relevant classes	41,691	8,276	35,708	13,732
Teachers linked to students	32,205	5,900	35,708	13,732
Eliminate charter school classes	22,254	4,660	34,012	13,322
Keep classes with 10-40 students who has no missing values on student and teacher variables	21,119	3,775	29,354	9,681

Table 2. Number of teachers who changed schools and/or changed settings during the study period, by state, level, mobility pattern and setting

	North Carolina		Florida	
	All Teachers	Teachers with 4 or more years of VA	All Teachers	Teachers with 4 or more years of VA
Elementary math teachers				
Total	21,119	6,712	29,989	7,720
School switchers	2,920	1,820	3,280	1,694
by school performance				
to a lower performing school	737	426	954	447
to a similar school	894	575	727	383
to a higher performing school	1,289	819	1,599	864
by school poverty				
to a higher poverty school	552	320	592	256
to a similar school	1,548	977	1,451	735
to a lower poverty school	820	523	1,237	703
Elementary reading teachers				
Total	21,119	6,712	29,354	7,145
School switchers	2,920	1,820	3,153	1,608
by school performance				
to a lower performing school	737	426	919	420
to a similar school	894	575	700	356
to a higher performing school	1,289	819	1,534	832
by school poverty				
to a higher poverty school	552	320	545	222
to a similar school	1,548	977	1,417	700
to a lower poverty school	820	523	1,191	686
Secondary math teachers				
Total	4,999	781	9,101	2,939
School switchers	544	215	987	575
by school performance				
to a lower performing school	187	66	311	164
to a similar school	122	57	196	115
to a higher performing school	235	92	480	296
by school poverty				
to a higher poverty school	108	34	202	103
to a similar school	345	136	581	347
to a lower poverty school	91	45	204	125
Secondary reading teachers				
Total	3,775	665	9,681	2,197
School switchers	373	163	809	396
by school performance				
to a lower performing school	95	39	272	122
to a similar school	66	28	145	65
to a higher performing school	212	96	392	209
by school poverty				
to a higher poverty school	82	38	164	71
to a similar school	243	104	471	233
to a lower poverty school	48	21	174	92

Table 3. Characteristics of teachers, by state, level and teacher mobility pattern
(Standard deviations in parentheses)

	Stayed in the same school next year	Moved to another school next year	Moved to a lower performing school	Moved to a higher performing school	Moved to a lower poverty school	Moved to a higher poverty school
North Carolina – Elementary Math						
Experience						
0-2 years	18.25	26.35	25.96	28.42	27.99	25.42
3-5 years	14.72	19.68	17.87	21.09	21.09	19.59
6-12 years	24.25	25.56	27.38	25.12	25.91	25.99
13 or more years	42.77	28.41	28.79	25.37	25.00	29.00
Regular license (%)	96.07	95.89	95.79	95.81	96.10	95.47
Graduate degree (%)	27.90	24.28	23.27	23.47	23.72	23.01
NBPTS certified (%)	5.68	5.28	4.75	5.62	4.65	3.44
Praxis score	0.07	0.09	0.03	0.12	0.10	0.05
Value added scores						
Gains model	0.00	-0.01	-0.02	0.00	0.00	-0.03
	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)
Levels, lag, lag^2	0.01	-0.01	-0.00	-0.01	-0.00	-0.02
	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)
Levels, lag and opposite subj lag)	-0.00	-0.02	-0.02	-0.02	-0.02	-0.04
	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)
North Carolina – Elementary Reading						
Experience						
0-2 years	18.26	26.35	25.96	28.42	27.99	25.42
3-5 years	14.72	19.68	17.87	21.09	21.09	19.59
6-12 years	24.25	25.56	27.38	25.12	25.91	25.99
13 or more years	42.77	28.41	28.79	25.37	25.00	29.00
Regular license (%)	96.07	95.89	95.79	95.81	96.10	95.47
Graduate degree (%)	27.90	24.28	23.27	23.47	23.72	23.01
NBPTS certified (%)	5.68	5.28	4.75	5.62	4.65	3.44
Praxis score	0.07	0.09	0.03	0.12	0.10	0.05
Value added scores						
Gains model	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Levels, lag, lag^2	0.01	-0.00	0.01	-0.01	-0.01	0.00
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)
Levels, lag and opposite subj lag)	0.00	-0.01	0.00	-0.01	-0.01	-0.01
	(0.08)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)

Table 3. Characteristics of teachers, by state, level and teacher mobility pattern—continued
(Standard deviations in parentheses)

	Stayed in the same school next year	Moved to another school next year	Moved to a lower performing school	Moved to a higher performing school	Moved to a lower poverty school	Moved to a higher poverty school
North Carolina – Secondary Math						
Experience						
0-2 years	14.34	17.54	15.91	20.91	19.77	22.77
3-5 years	13.43	17.15	15.91	17.27	13.95	15.84
6-12 years	25.63	28.65	29.55	27.73	33.72	23.76
13 or more years	46.60	36.65	38.64	34.09	32.56	37.62
Regular license (%)	92.75	92.83	93.05	91.06	92.31	89.81
Graduate degree (%)	30.92	24.91	27.03	25.86	24.44	23.36
NBPTS certified (%)	7.86	9.31	8.82	8.04	10.47	2.04
Praxis score	0.19	0.19	0.14	0.26	0.31	0.20
Value added scores						
Gains model	-0.02	-0.12	-0.15	-0.06	-0.23	-0.04
	(0.39)	(0.39)	(0.42)	(0.38)	(0.39)	(0.35)
Levels, lag, lag^2	-0.02	-0.10	-0.10	-0.08	-0.18	-0.06
	(0.35)	(0.34)	(0.36)	(0.34)	(0.36)	(0.32)
North Carolina – Secondary Reading						
Experience						
0-2 years	21.18	35.67	34.09	36.08	40.00	42.31
3-5 years	15.54	18.71	22.73	15.98	13.33	21.79
6-12 years	23.90	22.81	22.73	26.29	26.67	17.95
13 or more years	39.39	22.81	20.45	21.65	20.00	17.95
Regular license (%)	91.74	90.62	92.63	89.62	91.67	89.02
Graduate degree (%)	32.07	24.59	26.88	22.93	14.89	20.99
NBPTS certified (%)	8.78	7.10	4.40	8.63	4.35	5.00
Praxis score	0.24	0.26	0.18	0.25	0.30	0.31
Value added scores						
Gains model	0.00	0.01	0.01	0.01	-0.01	0.01
	(0.14)	(0.14)	(0.14)	(0.14)	(0.16)	(0.14)
Levels, lag, lag^2	-0.00	-0.01	-0.01	-0.01	-0.08	-0.01
	(0.17)	(0.17)	(0.18)	(0.17)	(0.18)	(0.18)

Table 3. Characteristics of teachers, by state, level and teacher mobility pattern—continued
(Standard deviations in parentheses)

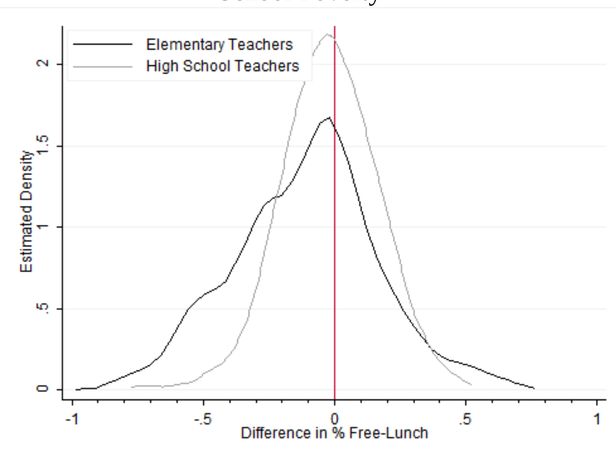
	Stayed in the same school next year	Moved to another school next year	Moved to a lower performing school	Moved to a higher performing school	Moved to a lower poverty school	Moved to a higher poverty school
Florida – Elementary Math						
Experience						
0-2 years	16.86	26.59	24.39	29.71	30.36	21.22
3-5 years	17.82	24.71	22.97	27.88	28.76	24.46
6-12 years	26.01	26.76	29.67	24.22	25.3	26.98
13 or more years	39.30	21.94	22.97	18.19	15.58	27.34
Graduate degree (%)	35.31	32.08	30.49	33.26	33.69	30.58
Value added scores						
Gains model	0.00	-0.01	-0.02	0.00	0.01	-0.04
	(0.17)	(0.18)	(0.17)	(0.18)	(0.18)	(0.16)
Levels, lag, lag^2	0.00	-0.02	-0.02	-0.03	-0.02	-0.04
	(0.18)	(0.18)	(0.17)	(0.19)	(0.19)	(0.17)
Levels, lag and opposite subj lag)	0.00	-0.02	-0.02	-0.02	-0.01	-0.04
	(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.17)
Florida – Elementary Reading						
Experience						
0-2 years	16.85	26.72	25.85	28.67	30.11	24.49
3-5 years	17.59	24.45	22.65	27.32	27.66	24.49
6-12 years	25.75	26.43	29.27	23.52	25.2	24.49
13 or more years	39.8	22.4	22.22	20.49	17.03	26.53
Graduate degree (%)	35.9	31.91	31.41	33.03	32.29	29.39
Value added scores						
Gains model	0.00	-0.01	-0.01	-0.01	-0.01	-0.02
	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
Levels, lag, lag^2	0.00	-0.02	-0.02	-0.03	-0.03	-0.02
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)
Levels, lag and opposite subj lag)	0.00	-0.01	-0.01	-0.02	-0.02	-0.02
	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)

Table 3. Characteristics of teachers, by state, level and teacher mobility pattern—continued
(Standard deviations in parentheses)

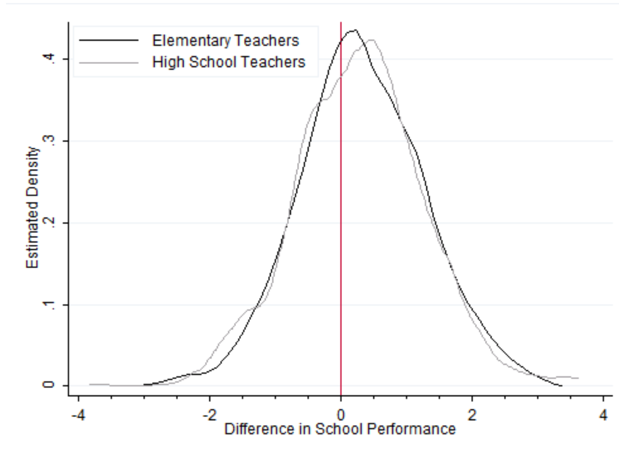
	Stayed in the same school next year	Moved to another school next year	Moved to a lower performing school	Moved to a higher performing school	Moved to a lower poverty school	Moved to a higher poverty school
Florida – Secondary Math						
Experience						
0-2 years	16.98	26.82	25.45	27.55	23.81	26.42
3-5 years	17.94	21.97	22.42	22.91	26.98	21.7
6-12 years	24.35	25.53	29.7	22.91	25.4	28.3
13 or more years	40.73	25.69	22.42	26.63	23.81	23.58
Graduate degree (%)	39.75	35.22	32.12	34.37	35.71	33.96
Value added scores						
Gains model	0.00	-0.00	-0.01	-0.00	-0.01	-0.01
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Levels, lag, lag^2	0.00	-0.03	-0.03	-0.04	-0.03	-0.02
	(0.14)	(0.14)	(0.15)	(0.13)	(0.12)	(0.15)
Levels, lag and opposite subj lag)	0.00	-0.02	-0.00	-0.03	-0.02	-0.02
	(0.13)	(0.13)	(0.15)	(0.13)	(0.12)	(0.15)
Florida – Secondary Reading						
Experience						
0-2 years	23.71	35.7	39.64	33.91	42.55	37.97
3-5 years	20.55	23.72	25.23	24.35	23.4	24.05
6-12 years	22.17	22.25	17.12	22.17	21.28	20.25
13 or more years	33.57	18.34	18.02	19.57	12.77	17.72
Graduate degree (%)	38.09	31.78	36.04	31.74	30.85	41.77
Value added scores						
Gains model	0.00	-0.01	-0.01	0.01	0.01	-0.01
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
Levels, lag, lag^2	0.00	-0.03	-0.03	-0.03	-0.03	-0.04
	(0.12)	(0.12)	(0.13)	(0.12)	(0.10)	(0.14)
Levels, lag and opposite subj lag)	0.00	-0.02	-0.02	-0.01	-0.02	-0.03
	(0.09)	(0.09)	(0.10)	(0.09)	(0.08)	(0.10)

Figure 1. Difference in school characteristics – Before and after the switch, math teachers

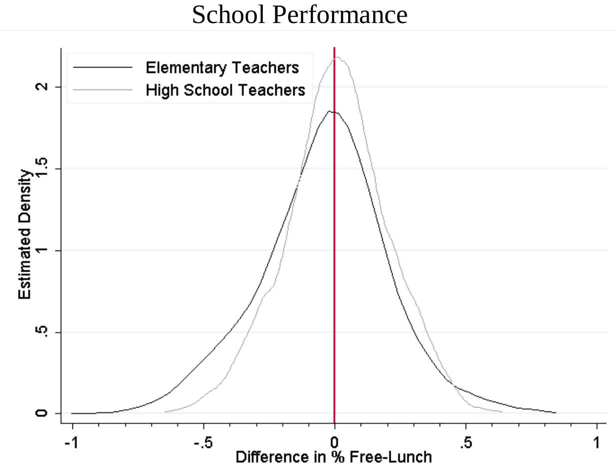
Florida
School Poverty



Florida
School Performance



North Carolina
School Performance



North Carolina
School Performance

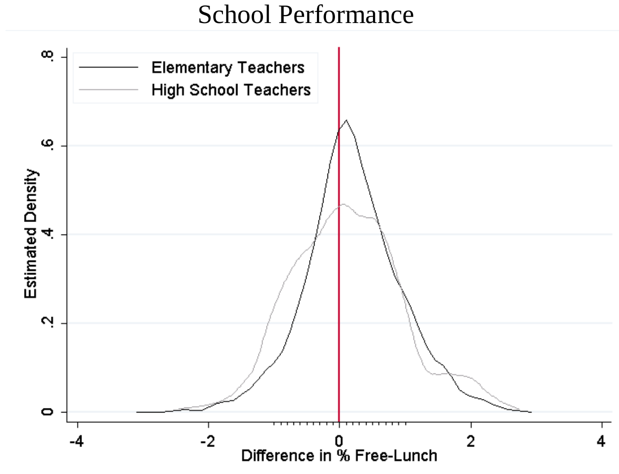
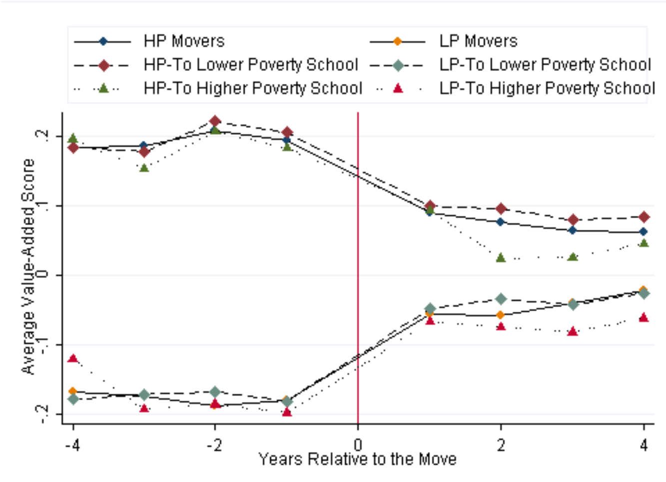
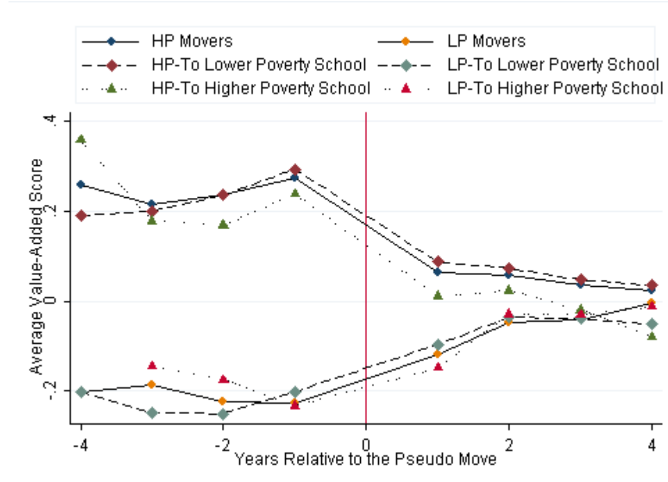


Figure 2. Teacher value-added – Years before and after the school switch, by teacher performance prior to the move, elementary math teachers

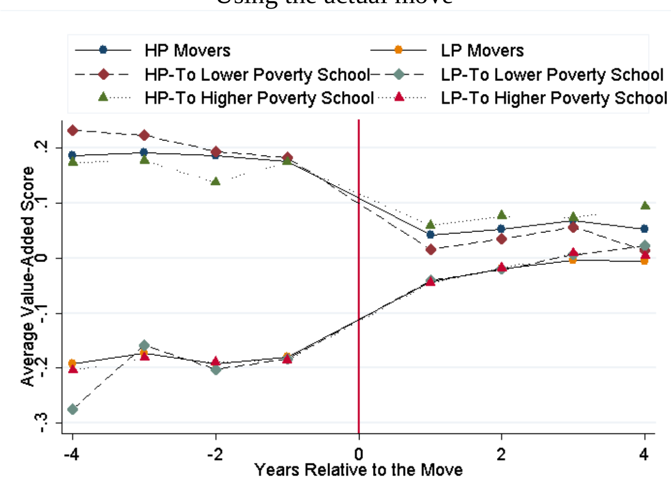
Florida
Using the actual move



Florida
Using the 'pseudo' move



North Carolina
Using the actual move



North Carolina
Using the 'pseudo' move

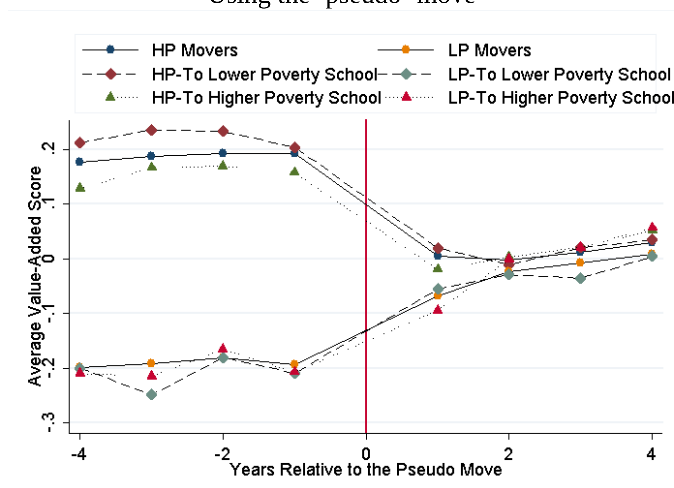


Table 4. Elementary school math teachers, by state, school setting and direction of move

	North Carolina				Florida			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Moved	0.001	0.004*			0.003	-0.001		
	(0.002)	(0.002)			(0.003)	(0.003)		
By school performance								
Moved to a lower performing school			0.018**	0.019**			0.006	0.002
			(0.004)	(0.004)			(0.005)	(0.005)
Moved to a similar school			0.001	0.004			0.004	0.007
			(0.003)	(0.003)			(0.004)	(0.005)
Moved to a higher performing school			-0.007**	-0.002			0.001	-0.005
			(0.003)	(0.003)			(0.003)	(0.003)
By school poverty								
Moved to a lower poverty school			-0.008*	-0.005			0.001	-0.004
			(0.003)	(0.003)			(0.004)	(0.004)
Moved to a similar school			0.001	0.005			0.004	0.000
			(0.003)	(0.003)			(0.004)	(0.004)
Moved to a higher poverty school			0.018**	0.020**			0.007	0.009
			(0.005)	(0.005)			(0.006)	(0.006)
School/classroom controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	60,698	60,064	60,698	60,064	36,205	35,202	36,205	35,202

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 5. Elementary school reading teachers, by state, school setting and direction of move

	North Carolina				Florida			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Moved	-0.000	0.005**			0.005*	0.002		
	(0.002)	(0.002)			(0.002)	(0.002)		
By school performance								
Moved to a lower performing school			0.008*	0.011**			0.004	0.002
			(0.003)	(0.003)			(0.004)	(0.004)
Moved to a similar school			-0.001	0.004			0.001	-0.001
			(0.003)	(0.003)			(0.004)	(0.005)
Moved to a higher performing school			-0.004	0.003			0.008**	0.004
			(0.002)	(0.002)			(0.003)	(0.003)
By school poverty								
Moved to a lower poverty school			-0.004	0.002			0.006*	0.002
			(0.003)	(0.003)			(0.003)	(0.003)
Moved to a similar school			-0.002	0.004*			0.004	0.002
			(0.002)	(0.002)			(0.003)	(0.003)
Moved to a higher poverty school			0.013**	0.017**			0.006	0.009
			(0.004)	(0.004)			(0.005)	(0.006)
School/classroom controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	60,692	60,058	60,692	60,058	33,753	33,753	33,753	33,753

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 6. Secondary school math teachers, by state, school setting and direction of move

	North Carolina				Florida			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Moved	0.032**	0.056**			0.002	0.003		
	(0.010)	(0.012)			(0.002)	(0.002)		
By school performance								
Moved to a lower performing school			0.050**	0.067**			-0.002	0.003
			(0.019)	(0.021)			(0.003)	(0.004)
Moved to a similar school			0.070**	0.085**			0.006	0.006
			(0.018)	(0.021)			(0.003)	(0.004)
Moved to a higher performing school			-0.003	0.030			0.002	0.002
			(0.013)	(0.018)			(0.003)	(0.003)
By school poverty								
Moved to a lower poverty school			0.090**	0.111**			0.003	0.002
			(0.021)	(0.027)			(0.004)	(0.004)
Moved to a similar school			0.038**	0.057**			0.003	0.004
			(0.013)	(0.015)			(0.002)	(0.002)
Moved to a higher poverty school			-0.038*	-0.010			-0.003	0.003
			(0.018)	(0.023)			(0.005)	(0.005)
School/classroom controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,887	6,977	9,887	6,977	14,465	14,463	14,465	14,463

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 7. Secondary school reading teachers, by state, school setting and direction of move

	North Carolina				Florida			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Moved	0.007	0.003			0.005	0.005		
	(0.006)	(0.007)			(0.003)	(0.003)		
By school performance								
Moved to a lower performing school			-0.021	-0.011			0.011*	0.013**
			(0.012)	(0.012)			(0.005)	(0.005)
Moved to a similar school			0.022*	0.014			0.005	0.008
			(0.011)	(0.013)			(0.006)	(0.007)
Moved to a higher performing school			0.013	0.005			0.002	0.0004
			(0.009)	(0.009)			(0.004)	(0.004)
By school poverty								
Moved to a lower poverty school			0.001	0.002			-0.004	-0.006
			(0.015)	(0.015)			(0.005)	(0.006)
Moved to a similar school			0.016	0.010			0.006	0.006
			(0.008)	(0.009)			(0.003)	(0.003)
Moved to a higher poverty school			-0.014	-0.020			0.014	0.019*
			(0.010)	(0.011)			(0.007)	(0.007)
School/classroom controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7,847	6,868	7,847	6,868	10,741	10,740	10,741	10,740

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 8. Elementary school math teachers with at least 2 pre-move years, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.098**	-0.078**	0.006*	0.078**	-0.066**	-0.01*
	(0.006)	(0.006)	(0.003)	(0.008)	(0.009)	(0.004)
By school performance						
Moved to a lower performing school	0.115**	-0.056**	0.021**	0.069**	-0.055*	-0.01
	(0.012)	(0.015)	(0.006)	(0.016)	(0.022)	(0.008)
Moved to a similar school	0.096**	-0.083**	0.004	0.089**	-0.067**	0.003
	(0.010)	(0.010)	(0.004)	(0.013)	(0.016)	(0.01)
Moved to a higher performing school	0.091**	-0.081**	0.001	0.078**	-0.07**	-0.015**
	(0.008)	(0.009)	(0.004)	(0.012)	(0.011)	(0.006)
By school poverty						
Moved to a lower poverty school	0.082**	-0.088**	0.004	0.089**	-0.065**	-0.013*
	(0.010)	(0.011)	(0.004)	(0.013)	(0.012)	(0.006)
Moved to a similar school	0.099**	-0.076**	0.003	0.073**	-0.08**	-0.006
	(0.007)	(0.009)	(0.003)	(0.011)	(0.012)	(0.007)
Moved to a higher poverty school	0.120**	-0.063**	0.020**	0.066**	0.002	-0.01
	(0.014)	(0.015)	(0.007)	(0.023)	(0.035)	(0.011)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9542	10565	35612	6,027	6,228	21,671

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 9. Elementary school reading teachers with at least 2 pre-move years, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.065**	-0.058**	0.010**	0.063**	-0.07**	0.002
	(0.005)	(0.005)	(0.002)	(0.007)	(0.009)	(0.004)
By school performance						
Moved to a lower performing school	0.078**	-0.046**	0.022**	0.056**	-0.087**	0.003
	(0.009)	(0.012)	(0.005)	(0.01)	(0.016)	(0.007)
Moved to a similar school	0.070**	-0.063**	0.008*	0.087**	-0.088**	-0.008
	(0.007)	(0.008)	(0.003)	(0.016)	(0.019)	(0.007)
Moved to a higher performing school	0.055**	-0.058**	0.006*	0.058**	-0.056**	0.006
	(0.007)	(0.007)	(0.003)	(0.009)	(0.012)	(0.005)
By school poverty						
Moved to a lower poverty school	0.056**	-0.068**	0.004	0.046**	-0.062**	0.007
	(0.008)	(0.007)	(0.003)	(0.01)	(0.012)	(0.005)
Moved to a similar school	0.065**	-0.055**	0.009**	0.078**	-0.075**	-0.004
	(0.006)	(0.007)	(0.003)	(0.009)	(0.014)	(0.006)
Moved to a higher poverty school	0.085**	-0.041**	0.024**	0.061**	-0.103**	0.003
	(0.011)	(0.011)	(0.006)	(0.016)	(0.029)	(0.01)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7786	8681	39244	6,234	6,486	21,206

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 10. Secondary school math teachers with at least 2 pre-move years, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.276**	-0.126*	0.106**	0.034**	-0.035**	0.005
	(0.033)	(0.050)	(0.022)	(0.005)	(0.006)	(0.003)
By school performance						
Moved to a lower performing school	0.304**	-0.165	0.125**	0.025*	-0.044**	0.013
	(0.048)	(0.107)	(0.039)	(0.011)	(0.012)	(0.007)
Moved to a similar school	0.213**	-0.056	0.090*	0.015	-0.014	0.006
	(0.048)	(0.070)	(0.041)	(0.017)	(0.011)	(0.006)
Moved to a higher performing school	0.342**	-0.129	0.100**	0.04**	-0.04**	0.001
	(0.054)	(0.068)	(0.031)	(0.006)	(0.007)	(0.005)
By school poverty						
Moved to a lower poverty school	0.349**	-0.113	0.112*	0.046**	-0.046**	-0.001
	(0.057)	(0.065)	(0.044)	(0.009)	(0.015)	(0.007)
Moved to a similar school	0.269**	-0.184**	0.143**	0.033**	-0.024**	0.003
	(0.042)	(0.057)	(0.025)	(0.007)	(0.006)	(0.004)
Moved to a higher poverty school	0.167**	-0.092	-0.006	0.024*	-0.076**	0.022**
	(0.056)	(0.097)	(0.046)	(0.011)	(0.016)	(0.008)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1536	1719	3097	2,096	2,303	10,453

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 11. Secondary school reading teachers with at least 2 pre-move years, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.084^{**}	-0.063^{*}	0.012	0.045^{**}	-0.039^{**}	0.004
	(0.021)	(0.027)	(0.014)	(0.006)	(0.009)	(0.005)
By school performance						
Moved to a lower performing school	0.099^{*}	-0.155^{**}	-0.004	0.045^{**}	-0.04	-0.002
	(0.047)	(0.051)	(0.026)	(0.007)	(0.031)	(0.007)
Moved to a similar school	0.076^{**}	-0.080	-0.004	0.054^{**}	0.018	0.005
	(0.022)	(0.047)	(0.015)	(0.016)	(0.031)	(0.011)
Moved to a higher performing school	0.131^{**}	-0.023	0.023	0.042^{**}	-0.042^{**}	0.007
	(0.047)	(0.033)	(0.018)	(0.011)	(0.01)	(0.006)
By school poverty						
Moved to a lower poverty school	0.104^{*}	-0.070	0.016	0.046^{*}	-0.07^{**}	0.006
	(0.048)	(0.056)	(0.021)	(0.023)	(0.015)	(0.007)
Moved to a similar school	0.091^{**}	-0.049	0.024	0.039^{**}	-0.019^{*}	0.002
	(0.025)	(0.035)	(0.018)	(0.007)	(0.007)	(0.006)
Moved to a higher poverty school	0.039	-0.105^{**}	-0.030	0.069^{**}	0.018	0.006
	(0.044)	(0.037)	(0.021)	(0.01)	(0.051)	(0.013)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1241	1345	3748	1,324	1,361	7,603

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 12. Elementary school math teachers with at least 2 pre-move years, pseudo move year test, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.062**	-0.051**	0.003	0.045**	-0.05**	-0.005
	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)
By school performance						
Moved to a lower performing school	0.077**	-0.032**	0.010*	0.045**	-0.04**	-0.015*
	(0.008)	(0.010)	(0.005)	(0.009)	(0.013)	(0.006)
Moved to a similar school	0.063**	-0.054**	0.002	0.053**	-0.052**	-0.001
	(0.005)	(0.006)	(0.004)	(0.007)	(0.01)	(0.007)
Moved to a higher performing school	0.055**	-0.054**	-0.001	0.042**	-0.052**	-0.002
	(0.005)	(0.006)	(0.003)	(0.006)	(0.006)	(0.004)
By school poverty						
Moved to a lower poverty school	0.055**	-0.061**	0.001	0.042**	-0.052**	0.003
	(0.007)	(0.007)	(0.004)	(0.006)	(0.007)	(0.005)
Moved to a similar school	0.062**	-0.048**	0.002	0.053**	-0.054**	-0.006
	(0.005)	(0.005)	(0.003)	(0.007)	(0.008)	(0.005)
Moved to a higher poverty school	0.074**	-0.039**	0.007	0.033**	-0.012	-0.022**
	(0.008)	(0.009)	(0.006)	(0.009)	(0.021)	(0.008)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9942	10825	34952	6,027	6,228	21,671

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 13. Elementary school reading teachers with at least 2 pre-move years, pseudo move year test, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.045**	-0.042**	-0.003	0.044**	-0.049**	-0.005
	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.003)
By school performance						
Moved to a lower performing school	0.060**	-0.031**	0.014**	0.042**	-0.057**	-0.006
	(0.007)	(0.008)	(0.004)	(0.006)	(0.009)	(0.005)
Moved to a similar school	0.045**	-0.043**	0.001	0.059**	-0.057**	-0.017**
	(0.004)	(0.005)	(0.003)	(0.008)	(0.011)	(0.006)
Moved to a higher performing school	0.039**	-0.046**	0.003	0.04**	-0.042**	0.001
	(0.004)	(0.005)	(0.002)	(0.005)	(0.006)	(0.003)
By school poverty						
Moved to a lower poverty school	0.039**	-0.053**	0.002	0.04**	-0.048**	-0.002
	(0.005)	(0.005)	(0.003)	(0.005)	(0.007)	(0.004)
Moved to a similar school	0.047**	-0.038**	0.005*	0.049**	-0.047**	-0.005
	(0.004)	(0.004)	(0.002)	(0.005)	(0.008)	(0.004)
Moved to a higher poverty school	0.054**	-0.034**	0.010*	0.043**	-0.062**	-0.012
	(0.007)	(0.008)	(0.005)	(0.007)	(0.016)	(0.007)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8318	9118	38275	3,697	8,069	21,987

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 14. Secondary school math teachers with at least 2 pre-move years, pseudo move year test, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.168**	-0.089**	0.071**	0.025**	-0.025**	0.003
	(0.022)	(0.032)	(0.016)	(0.004)	(0.004)	(0.003)
By school performance						
Moved to a lower performing school	0.200**	-0.057	0.070**	0.026**	-0.033**	0.005
	(0.033)	(0.055)	(0.022)	(0.005)	(0.009)	(0.004)
Moved to a similar school	0.121**	-0.085	0.127**	0.027**	-0.012	0.0004
	(0.032)	(0.073)	(0.028)	(0.007)	(0.006)	(0.006)
Moved to a higher performing school	0.176**	-0.106*	0.094**	0.025**	-0.026**	0.002
	(0.040)	(0.042)	(0.018)	(0.005)	(0.006)	(0.003)
By school poverty						
Moved to a lower poverty school	0.190**	-0.052	0.131**	0.024**	-0.034**	0.0002
	(0.060)	(0.028)	(0.024)	(0.008)	(0.012)	(0.004)
Moved to a similar school	0.180**	-0.095*	0.093**	0.024**	-0.017**	0.001
	(0.026)	(0.041)	(0.016)	(0.004)	(0.004)	(0.003)
Moved to a higher poverty school	0.094*	-0.080	0.054	0.032**	-0.047**	0.011
	(0.041)	(0.063)	(0.032)	(0.007)	(0.012)	(0.006)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1547	1719	3086	2,096	2,303	10,453

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 15. Secondary school reading teachers with at least 2 pre-move years, pseudo move year test, by state, teacher's pre-move performance, school setting and direction of move

	North Carolina			Florida		
	Low-performer	High-performer	Average	Low-performer	High-performer	Average
Moved	0.063**	-0.053*	0.001	0.027**	-0.025**	-0.002
	(0.018)	(0.023)	(0.011)	(0.004)	(0.007)	(0.003)
By school performance						
Moved to a lower performing school	0.093**	-0.142**	0.008	0.028**	-0.022*	-0.006
	(0.029)	(0.045)	(0.023)	(0.005)	(0.012)	(0.005)
Moved to a similar school	0.048**	-0.083*	-0.004	0.026**	-0.028	-0.003
	(0.017)	(0.036)	(0.016)	(0.007)	(0.019)	(0.009)
Moved to a higher performing school	0.069*	-0.034	0.016	0.026**	-0.025**	0.001
	(0.030)	(0.026)	(0.015)	(0.009)	(0.008)	(0.005)
By school poverty						
Moved to a lower poverty school	0.070**	-0.005	-0.038*	0.018	-0.032*	-0.003
	(0.017)	(0.005)	(0.018)	(0.01)	(0.013)	(0.007)
Moved to a similar school	0.067**	-0.047	0.018	0.025**	-0.021**	-0.002
	(0.022)	(0.026)	(0.013)	(0.005)	(0.008)	(0.004)
Moved to a higher poverty school	0.024**	-0.122**	0.010	0.044**	-0.017	-0.001
	(0.007)	(0.032)	(0.026)	(0.008)	(0.01)	(0.009)
School/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1266	1321	3747	1,203	1,844	7,693

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 16. Adjacent year teacher VA correlations for elementary school movers with at least 2 pre-move and 2 post-move years, by state and subject
(95% confidence interval in parentheses)

	North Carolina		Florida	
	Math	Reading	Math	Reading
Elementary school				
Corr(t-2, t-1)	0.483	0.298	0.380	0.187
	(0.426, 0.535)	(0.232, 0.362)	(0.314, 0.443)	(0.111, 0.260)
Corr(t-1, t+1)	0.341	0.270	0.302	0.138
	(0.256, 0.420)	(0.182, 0.354)	(0.231, 0.369)	(0.061, 0.213)
Corr(t+1, t+2)	0.463	0.269	0.427	0.191
	(0.381, 0.537)	(0.175, 0.358)	(0.363, 0.487)	(0.115, 0.264)

Table 17. Pre-move and post-move average VA for movers with at least 2 pre-move years, by state and teacher's pre-move performance
(Standard deviation in parentheses)

	North Carolina		Florida	
	Pre-move	Post-move	Pre-move	Post-move
Elementary math				
High performer	0.153	0.054	0.172	0.078
	(0.130)	(0.143)	(0.137)	(0.160)
Low performer	-0.160	-0.021	-0.160	-0.059
	(0.116)	(0.114)	(0.120)	(0.156)
Elementary reading				
High performer	0.073	0.019	0.088	0.026
	(0.064)	(0.066)	(0.069)	(0.097)
Low performer	-0.076	-0.012	-0.081	-0.019
	(0.063)	(0.068)	(0.064)	(0.091)
Secondary math				
High performer	0.239	0.126	0.067	0.017
	(0.269)	(0.232)	(0.056)	(0.069)
Low performer	-0.193	0.005	-0.053	-0.022
	(0.260)	(0.255)	(0.046)	(0.064)
Secondary reading				
High performer	0.115	0.048	0.056	0.005
	(0.099)	(0.152)	(0.058)	(0.073)
Low performer	-0.138	-0.069	-0.064	-0.004
	(0.094)	(0.144)	(0.046)	(0.068)