

NBER WORKING PAPER SERIES

WHO LEAVES? TEACHER ATTRITION AND STUDENT ACHIEVEMENT

Donald Boyd
Pam Grossman
Hamilton Lankford
Susanna Loeb
James Wyckoff

Working Paper 14022
<http://www.nber.org/papers/w14022>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2008

We are grateful to the New York City Department of Education and the New York State Education Department for the data employed in this paper. We appreciate comments on an earlier draft from Tim Sass, Jonah Rockoff and participants at both the Economics of Teacher Quality Conference at the Australian National University and the New York Federal Reserve Education Policy Workshop. The research is supported by funding from the Carnegie Corporation of New York, the National Science Foundation, the Spencer Foundation and the National Center for the Analysis of Longitudinal Data in Education Research (CALDER). The views expressed in the paper are solely those of the authors and may not reflect those of the funders. Any errors are attributable to the authors. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2008 by Donald Boyd, Pam Grossman, Hamilton Lankford, Susanna Loeb, and James Wyckoff. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Who Leaves? Teacher Attrition and Student Achievement

Donald Boyd, Pam Grossman, Hamilton Lankford, Susanna Loeb, and James Wyckoff
NBER Working Paper No. 14022

May 2008

JEL No. I21,J24

ABSTRACT

Almost a quarter of entering public-school teachers leave teaching within their first three years. High attrition would be particularly problematic if those leaving were the more able teachers. The goal of this paper is estimate the extent to which there is differential attrition based on teachers' value-added to student achievement. Using data for New York City schools from 2000–2005, we find that first-year teachers whom we identify as less effective at improving student test scores have higher attrition rates than do more effective teachers in both low-achieving and high-achieving schools. The first-year differences are meaningful in size; however, the pattern is not consistent for teachers in their second and third years. For teachers leaving low-performing schools, the more effective transfers tend to move to higher achieving schools, while less effective transfers stay in lower-performing schools, likely exacerbating the differences across students in the opportunities they have to learn.

Donald Boyd
The Center for Policy Research
University of Albany
Milne 300
135 Western Ave.
Albany, NY 12222
boydd@rockinst.org

Pam Grossman
School of Education
Stanford University
Stanford, CA 94305
Pamg@stanford.edu

Hamilton Lankford
School of Education, ED 317
University at Albany
State University of New York
Albany, NY 12222
hamp@albany.edu

Susanna Loeb
524 CERAS, 520 Galvez Mall
Stanford University
Stanford, CA 94305
and NBER
sloeb@stanford.edu

James Wyckoff
Curry School of Education
University of Virginia
P.O. Box 400277
Charlottesville, VA 22904-4277
wyckoff@virginia.edu

I. Introduction

Almost a quarter of entering public-school teachers leave teaching within their first three years (U.S. Department of Education, 2007). The rates are higher in schools with low academic achievement, leading many policymakers to the conclusion that to improve student performance, policies must focus on improving teacher retention. High attrition would be particularly problematic if those leaving were the more able teachers. While teachers who have stronger academic backgrounds, as measured by test scores and the competitiveness of their undergraduate institution, are more likely to leave teaching (Boyd, Lankford, Loeb and Wyckoff, 2005), there is remarkably little evidence that documents the *effectiveness* of teachers who leave low-scoring schools. This paper generates estimates of novice teachers' value-added to student test score gains in New York City (NYC) that allow us to assess the relative effectiveness of teachers who stay in their original school, transfer within NYC, transfer to another New York State (NYS) district, or leave teaching in NYS public schools. We pay particular attention to attrition patterns in lower-scoring schools and, for the teachers in these schools who transfer within the NYC public system, differences between the schools to which the relatively more and less effective teachers transfer.

Teacher retention may affect student learning in several ways. First, in high-turnover schools, students may be more likely to get inexperienced teachers who we know are less effective, on average (Rockoff, 2004; Rivkin, Hanushek and Kain 2005; Kane, Rockoff and Staiger, 2006). Second, high turnover creates instability in schools making it more difficult to have coherent instruction. This instability may be particularly problematic when schools are trying to implement reforms, as the new teachers coming in each year are likely to repeat mistakes rather than improve upon implementation of reform. Third, high turnover can be costly in that it takes time and effort to continuously recruit teachers. In addition to all these factors, turnover can reduce student learning if more effective teachers are the ones more likely to leave.

Recent research has dramatically increased our understanding of teacher retention (e.g., Ingersoll, 2001, 2004; Ingersoll and Kralik, 2004; Ingersoll & Smith, 2003 and 2004; Hanushek, Kain and Rivkin, 2004; Johnson, 2004; Boyd, Lankford, Loeb, & Wyckoff, 2005; Loeb, Darling-Hammond, & Luczak, 2005). These studies show that teacher mobility differs both by teacher characteristics and by the characteristics of their students. Teachers are more likely to stay in schools in which student achievement is higher and teachers – especially white teachers – are more likely to stay in schools with higher proportions of white students. Teachers who score higher on tests of academic achievement are more likely to leave, as are teachers whose home

town is farther from the school in which they teach. Attributes of teachers and the students they teach appear to interact. In particular, teachers having stronger qualifications (as measured by scores on a general knowledge certification exam) are more likely to quit or transfer than are less-qualified teachers, especially if they teach in low-achieving schools (Boyd, Lankford, Loeb and Wyckoff, 2005).

Reducing teacher attrition might help improve the teacher workforce; however, whether this is actually the case is an open question. How teacher attrition affects the quality of the teacher workforce depends upon a number of factors, including the typical gains in effectiveness teachers realize from additional years of experience, how the average quality of entering cohorts of teachers differ from those who entered the profession earlier, and how turnover affects the functioning of the school and in turn the effectiveness of other teachers. A crucial factor is whether those teachers who leave teaching are more or less effective than their peers who remain. Research on the relationship of teacher attrition and teacher effectiveness is just now emerging. Hanushek, Kain, O'Brien and Rivkin (2005) find that the teachers leaving schools in an urban Texas district on average have lower student achievement gains than do the teachers who remain in the same school. This is true for those transferring within the district as well as those leaving. They find that the differences in teacher effectiveness are greater for teachers making intra-district transfers following their second and third years of teaching. Goldhaber, Gross and Player (2007) also find that the teachers who transfer and leave teaching are less effective than those who remain.

The goal of this paper is to supplement this early evidence regarding whether and how the effectiveness of teachers differ by their retention status. We do this by looking specifically at how differential attrition varies across schools and grade levels during a teacher's first three years of teaching and by following teachers who transfer to assess the extent to which more and less effective teachers sort systematically into differing types of schools. Using data for New York City schools from 2000–2005, we find that teacher attrition rates are significantly higher in schools with lower student achievement. In addition, the first-year teachers that we identify as less effective in improving student test scores have higher attrition rates than do more effective teachers in both low-achieving and high-achieving schools. The first-year differences are meaningful in size; however, the pattern is not consistent for teachers in their second and third years. For teachers leaving low-performing schools, the more effective transfers tend to move to higher achieving schools, while less effective transfers stay in lower-performing schools, likely exacerbating the differences across students in the opportunities they have to learn and to meet their own goals as well as those set by the city and state.

II. Teacher Attrition and Student Performance: Data and Methods

We classify individuals as remaining in the same school, transferring to another school within NYC, transferring to another public school district in New York or leaving the New York State public school system. This last category includes individuals who have quit teaching, as well as those who took teaching jobs in private schools or in public schools in other states. Figure 1 shows the cumulative transition rates for entering cohorts of NYC teachers in grades four through eight who started teaching between 2000 and 2003.¹ After three years slightly more than a quarter of the teachers had left the NYS public school system and another eight percent were teaching in other school districts in New York State. Twenty percent of the entering teachers were teaching in another school within NYC.² The net result was that by the start of the fourth year only 46 percent of teachers continue to teach in the same school where they began their careers.

Even though the school-level attrition for second-year teachers is almost as great as that for first-year teachers (17 v. 20 percent), there are meaningful differences in destinations of the teachers who leave. More than half of the teachers who leave following their first year transfer to another school within New York City, a third leave the New York State system (e.g., quit teaching) and only 15 percent transfer to the suburbs. Among those leaving their initial school placement after the second year, only 27 percent transfer within New York City and more than half leave the New York State system.

Much of the discussion regarding teacher retention is from a system-wide perspective, asking what percentage of teachers leave the profession overall. However, it is understandable that those specifically interested in educational outcomes in New York City (or any other specific district) take a narrower view, being concerned about those who transfer out of their school system, as well as those who leave the profession. From an even more local perspective, school principals, parents and others likely will have a school-level perspective, primarily concerned with teacher turnover in particular schools. A school-level perspective has broad policy interest as well, given the systematic sorting of students and teachers across schools. There are large differences in both student achievement and teacher characteristics across schools. Interest in improving outcomes for low-performing students often means focusing at the school level.

¹ We stop with the 2003 cohort so that we can follow the teachers for three years to determine whether they have left teaching.

² The 20 percent figure does not include the additional roughly one percent of teachers who transferred within NYC but subsequently transferred to another district or quit teaching.

The effectiveness of teachers accounts for a substantial share of the variance in student learning after students' own attributes have been taken into account (Sanders and Rivers, 1996). Teachers in schools with the highest proportions of low-performing students are less qualified as measured by certification status, their own exam performance, and teaching experience than are those in better performing schools (Betts, Reuben & Danenberg , 2000; Lankford, Loeb and Wyckoff, 2002; Clotfelter, Ladd, Vigdor & Wheeler, 2007; Peske & Haycock 2006). However, teacher qualifications are not synonymous with teacher effectiveness. We have little information on how teachers' actual effectiveness differs across schools.

Determining whether teachers in schools with low performing students are less able than teachers in other schools is not an easy task. When teachers teach similar students, it is relatively easy to see whether students learn more in one teacher's classroom than in another's. However, when teachers teach systematically different students or in different schools, it is not clear whether to attribute differences in student learning to the teachers or to other factors. While we cannot say definitively whether teachers in one school are more effective than teachers in another, we do explore whether more effective teachers within each school stay or leave and whether such within-school differences in attrition differs systematically across schools.

Data: Our analyses draw on a rich database constructed from administrative data from the New York City Department of Education and the New York State Education Department. Over the years included in the analysis, New York State gave statewide student exams in mathematics and English language arts in grades four and eight. In addition, the New York City Department of Education tested third, fifth, sixth and seventh graders in these subjects. All the exams are aligned to the New York State learning standards and each set of tests is scaled to reflect item difficulty, and are equated across grades and over time.³ Tests are given to all registered students with limited accommodations and exclusions. Thus, for nearly all students, the tests provide a consistent assessment of achievement for a student from grade three through grade eight.

To analyze the contributions of teachers to student achievement, we create a student database with student exam scores, lagged scores and characteristics of students and their peers linked to their schools and teachers. The student data, provided by the New York City

³ The mathematics exams in all grades are developed by CTB-McGraw Hill. New York State employs CTBMcGraw Hill for its 4th and 8th grade ELA exams. In 2003 New York City switched from CTB to Harcourt Brace for its 3rd, 5th-7th grade exams. At that time there was an equating study done to accommodate the switch in exams.

Department of Education (NYCDOE), consists of a demographic data file and an exam data file for each year from 1998-99 through 2004-05. The demographic files include measures of gender, ethnicity, language spoken at home, free-lunch status, special-education status, number of absences, and number of suspensions for each student who was active in grades three through eight that year – approximately 450,000 to 500,000 students each year. More detail is provided in the Appendix.

The exam files include, among other things, the year in which an exam was given, the grade level of the exam, and each student's scaled score on the exam. For most years, the file contains scores for approximately 65,000 to 80,000 students in each grade. The only significant exception is that the files contain no scores for 7th grade English language arts in 2002 because the New York City Department of Education is not confident that exam scores for that year and grade were measured in a manner that was comparable to the 7th grade English language arts exam in other years.

Using these data, we construct a student-level database where exam scores are normalized for each subject, grade and year to have a zero mean and unit standard deviation, to accommodate any year-to-year or grade-to-grade anomalies in the exam scores. For this purpose, we consider a student to have gain-score information in cases in which he/she has a score in a given subject (ELA or math) for the current year and a score for the same subject in the immediately preceding year for the immediately preceding grade. We do not include cases in which a student took a test for the same grade two years in a row, or where a student skipped a grade.

To enrich our data on teachers, we match New York City teachers to data from New York State Education Department (NYSED) databases, using a crosswalk file provided by NYCDOE that links their teacher file reference numbers to unique identifiers compatible with both databases. We drew variables for NYC teachers from these data files as follows:

- **Teacher Experience:** For teacher experience, we use transaction data from the NYCDOE Division of Human Resources payroll system to calculate experience in teaching positions in the New York City public school system. This is supplemented using NYSED data on whether teachers previously taught in other public school districts in New York. Teachers are included in the retention analysis only if they first taught in NYC during the period analyzed and had not previously taught in another NYS district.
- **Attrition:** We used the NYCDOE transaction data to identify the schools where novice teachers initially taught and, in subsequent years, whether they continue to teach in the same, or some other, NYC school. For those teachers who left the NYC public system,

NYSED data is used to determine which of these individuals transferred to another district in New York.

Finally, we match teachers and students to their schools, and incorporate data on those schools from the New York City Department of Education Annual School Report database, including:

- School-average performance on state and city standardized exams
- Poverty status as measured by the percentage of students eligible for Free and Reduced-Price Lunch
- Racial and ethnic breakdown of students

The analysis of teacher retention links teachers to schools and places schools into categories based on average student math scores. In defining groups, we weight each school by the number of teachers in our data, so that a school with many teachers will count more than a school with few teachers.

Measuring Teacher Effectiveness: A student's acquisition of skills and knowledge is a complex social enterprise producing a variety of outcomes for students. This paper focuses on the specific outcomes of test-score gains in math and English language arts (ELA) in grades four through eight. Teachers clearly affect students more broadly than is measured on these exams. Thus the analyses in this paper do not fully account for all the contributions that teachers make to students. Nonetheless, these scores are a reasonable metric for measuring part of teacher effectiveness, both because they are the State's chosen measure of student learning and because similar measures of achievement increasingly have been found to be strong predictors of students' later educational and economic success (Murnane, Willett, Duhldeborde, and Tyler, 2000).

Even when limiting the analysis to achievement gains in math and English language arts, disentangling the contributions of a particular teacher from the contributions of other school inputs and the range of other determinants (e.g., home influences) is a challenge. We estimate the effectiveness of teachers in improving the educational outcomes of students using the fairly typical value-added model shown in Equation 1. Y_{ijst} is the test score of the i^{th} student taught by the j^{th} teacher in school s during year t . We separately analyze scores in math and ELA.⁴

$$Y_{ijst} = X_{it}\alpha + C_{jt}\beta + \delta_s + \gamma_{jt} + \varepsilon_{ijst} \quad (1)$$

To net out the effects of a student's own background and past academic achievement, the vector of student attributes, X_{it} , includes measures indicating the student's poverty status, whether the student is an English language learner, the student's race, school absences and

⁴ Test scores are normalized by grade and year to have zero means and standard deviations of one.

suspensions in the prior year, whether the student transferred from another school as well as the students' scores on both the math and ELA exams in the prior grade and those scores squared. C_{jt} includes averages of these same variables for the student's classmates. To capture the wide range of school-level factors affecting student outcomes, we include school fixed-effects, δ_s . We account for these various factors in an effort to isolate the value-added by a student's teacher, here measured by γ_{jt} . Note that this is a teacher-year fixed effect which is estimated separately for each year a person teaches and that estimates of the γ_{jt} only provide information about a teacher's effectiveness relative to other teachers in the same school, as a result of the model including school fixed-effects. Finally, ε_{ijst} is an error term capturing other factors affecting a student's score (e.g., test measurement error).

Descriptive statistics for the variables included in the value-added models are reported in the Appendix, along with parameter estimates for the four models. That is, we estimate models that yield both math and ELA value-added estimates for fourth- and fifth-grade teachers and value-added estimates for both math and ELA teachers in middle-schools. These teacher-by-year fixed-effect estimates are estimated for all teachers in these grades and subjects. However, the retention analysis focuses upon teachers in their first three years of teaching.

With the inclusion of the many student, class and school controls, the estimated teacher-year effects aim to measure within-school differences in teachers' effectiveness at improving the test performance of students.⁵ Even so, as estimates, the fixed-effects are subject to statistical error so that part of the observed variation is due to measurement error, not actual differences in the effectiveness of teachers. We employ the empirical Bayes approach to adjust the teacher-effect estimates for such estimation error.⁶ We use with-in school differences in these adjusted fixed-effects by level of experience as our measure of teacher effectiveness.⁷ For example, our measure of a sixth, seventh or eighth grade, second-year teacher in math is calculated as the difference between the teacher's adjusted fixed effect and the average of the adjusted fixed-effects for all the second-year math teachers who taught in that same school

⁵ An alternative would have been to explicitly model the gains from experience and estimate teacher effects, instead of teacher-year effects. We chose the latter because of our focus on teachers in the first few years of their careers and our decision to compare teachers only to other teachers in their same school having the same level of experience.

⁶ See Jacob and Lefgren (2005) for a clear summary of the approach we use as well as Kane and Staiger (2002) and Morris (1983) for earlier references.

⁷ From the empirical-Bayes-adjusted estimate of a teacher's effectiveness in a particular year we subtracted the mean adjusted estimate for all teachers in the school having the same level of experience. It is these normalized, adjusted estimates of within school (and experience level) differences in teacher effectiveness we utilize in the remainder of the paper.

during the period 2000-2005. This approach yields fairly clean estimates of how effective each teacher is relative to their equally experienced peers in the same school.

Because most fourth and fifth grade teachers teach both math and ELA, it is possible to estimate measures of effectiveness for these teachers in both subject areas. In this analysis teacher effectiveness has a mean of zero for teachers in the same school and with the same experience, due to the normalization described above. For first-year teachers in these grades, the standard deviation of our measure of effectiveness is 0.13 in math and 0.10 in ELA. The correlation between the effectiveness measures for math and ELA for fourth and fifth grade teachers in their first year is 0.47, indicating that teachers good in one area are generally effective in the other but that many teachers are relatively better in one area. The student test score itself is measured in standard deviation units so that a one standard deviation difference in math effectiveness corresponds to a .132 standard deviation difference in student test performance. The standard deviation of the gain in student test scores is somewhat lower at approximately 0.6, so that a standard deviation difference in teacher effectiveness corresponds to approximately 0.2 standard deviation change in student learning over the course of a year.

The results for the middle-school grades are similar. The standard deviation of our measure of effectiveness in grades sixth through eight is 0.10 in math and 0.08 in ELA. Because of course specialization at the middle-school level, only 20 percent of the sixth through eighth grade teachers in our sample teach both subjects. For them, the effectiveness measures for the two subjects have a correlation of 0.38.⁸

III. Teacher Attrition and Teacher Effectiveness in New York City

Teacher attrition for novice teachers in New York City is marked by two dominant themes. First, teachers of low-performing students are more likely to leave their current schools during their first two years of teaching than are teachers of high-performing students. And, second, across both low and high-performing schools, teachers who are less effective in raising student achievement are more likely to leave their current school than are more effective teachers. These results hold up across grade levels and across schools grouped by the performance of students in math or ELA. The results are stronger for teacher effectiveness measured by math than by ELA value-added. The exception is middle-school ELA teachers where there appears to be no relationship between teacher effectiveness and retention.

⁸ The standard deviations for the test groupings are roughly comparable to those reported by Rockoff (2004) and smaller than those reported by Hanushek, Kain, O'Brien and Rivkin (2005) as well as Jacob and Lefgren (2005).

Teachers in low-performing schools more likely to leave. Figure 2 shows attrition patterns for teachers by school average achievement scores. The category *higher-scoring schools* includes the quartile of schools having the highest mean math scores, while the *lower-scoring* category includes the quartile of schools having the lowest mean math scores. The *middle-scoring* group consists of schools in the middle 50 percent.⁹ In both the first and second year, we observe a greater proportion of teachers leaving the lower-scoring schools, compared to teachers in higher-scoring schools; the lower-scoring schools have higher transfer rates within NYC as well as relatively more teachers leaving the NYS system. The net result is that, by the end of the second year, the difference in school-level attrition is eight percentage points (38 vs. 30 percent). When schools are grouped based on either student poverty measured by free-lunch eligibility or the percent of students who are either Black or Hispanic, the patterns of school-level attrition are very similar. For example, when schools are grouped by the percent of minority students, the difference in the cumulative two-year school-level attrition rate is nine percentage points (39 vs. 30 percent) between top and bottom quartiles. When schools are grouped based on student poverty, there is a six percentage point difference. Furthermore, the attrition patterns for the separate transitions (e.g., leaving the NYS system) are quite similar whether schools are grouped based on student scores, race or poverty.

Less-effective novice teachers more likely to leave – 4th and 5th grade results.

Figure 3a displays attrition rates for fourth- and fifth-grade teachers grouped according to whether their value-added is in the top or bottom quartile or the middle half. First-year teachers with relatively low math value-added are more likely both to transfer to another school within NYC and to leave the NYS system, compared to their more effective peers. Twenty-three percent of first-year teachers whose math value-added is in the bottom quartile transfer or leave teaching, while only 15 percent of those in the top-quartile do so. The differences for second-year teachers are much smaller. The differences in attrition rates also are smaller when teacher effectiveness is measured using ELA value-added rather than that for math. (See Figure 3b.)

The patterns evident in Figures 3a and 3b come through in multivariate analysis, as well. A multivariate approach has the benefit of being able to account for school-specific differences in attrition as well as possible interactions between school type and teacher effectiveness. Equation 2 describes the basic model. Here the probabilities of returning to the same school the following year ($h=1$), transferring to another NYC school ($h=2$), transferring to another NYS

⁹ Schools here are grouped based on the mean math scores of fourth- and fifth-grade students and weighted by student enrollment in those grades. Similar groupings are employed for middle schools.

district (h=3) and leaving the NYS public system (h=4) are a function of E_j representing either a scalar or vector

$$P_j^h = \frac{\exp(\alpha_s^h + \beta^h E_j)}{\sum_g \exp(\alpha_s^g + \beta^g E_j)}, \quad h = 1, 2, 3, 4 \quad (2)$$

measure of teacher effectiveness. The α_s^h are school-specific constant terms that capture the general attrition patterns in each school. This fixed-effect multinomial logit specification is attractive in that we need not estimate the school fixed effects. Rather they can be swept from the model, allowing us to focus on estimating how within-school differences in teacher effectiveness explain which teachers in a school leave conditional on the schools' overall attrition rates.¹⁰ Without loss of generality, we employ the normalizations $\alpha_s^1 = \beta^1 = 0$. Thus, by estimating the parameters β^2 , β^3 and β^4 , we can make inferences regarding how the transition probabilities within a school vary with the relative effectiveness of teachers.¹¹ A word of caution is warranted here in that non-zero values of the β^h 's do not necessarily imply a causal relationship. We are merely interested in obtaining a clearer empirical description of how attrition varies with teachers' own effectiveness. Additional information regarding the estimation strategy is provided in the Appendix.

Parameter estimates for several different specifications for fourth- and fifth-grade teachers are shown in the top panel of Table 1.¹² Model A, estimated for teachers having up to three years of experience, indicates that less effective teachers are more likely to transfer within

¹⁰ Estimating the conditional logit model allows us to avoid the incidental-parameters problem; if the school-specific constants were estimated along with the effective coefficients, the latter estimates would be biased. See Chamberlain (1980).

¹¹ Because all the β^h 's enter the formula for each of the transition probabilities, interpreting the estimated coefficients is somewhat complicated. However, given the normalization we employ, it follows that $P_j^h / P_j^1 = \exp(\alpha_s^h) \exp(\beta^h E_j)$. Thus, a negative value of β^h would indicate that an increase in teacher effectiveness is associated a reduction in the probability of transition h relative to the probability of remaining in the same school. Note that the magnitude of the effect depends upon β^h as well as the school's baseline pattern of transition, captured by the school fixed effect, α_s^h ; in particular, the magnitude of the effect of an increase in E_j will be larger as $\exp(\alpha_s^h)$ is larger.

¹² N = 3192 shown in the top panel of Table 1 is the number of entering novice teachers included in the analysis. In specifications where second- and third-year teachers enter the analysis, the number of observations exceed N since many of these teachers teach multiple years.

The models estimated are somewhat more complicated than the specification shown in (2). In particular, we included alternative-specific dummy variables indicating one's years of experience beyond the first year, in order to account for the fact that transition patters for teachers in their second and third years might well differ systematically from those for first-year teachers.

NYC compared to more effective teachers. There is a similar inverse relationship for the probability of leaving the NYS system. In contrast, we find no systematic relationship between the transition probabilities and individuals' effectiveness in teaching ELA. The estimated coefficients are small in magnitude relative to those estimated for math, and their standard errors are somewhat larger. We estimate a range of different specifications, but never find evidence of a systematic relationship between the transition probabilities and fourth- and fifth-grade teachers' effectiveness in ELA, except in the case where math effectiveness is dropped from the model. In light of this finding, ELA effectiveness is not included in the other specifications reported for teachers in grades four and five.

We also explore whether the systematic pattern for math effectiveness holds equally for first, second and third year teachers and find that it does not. Model B shows the pattern for first-year teachers is as just noted. However, the second row of Model B shows that there is no evidence of a systematic relationship between math effectiveness and the transition probabilities for second- and third-year teachers. We estimate a range of models and find this result to be robust. For example, for second- and third-year teachers, we estimate models (not shown) that include variables reflecting their current and/or first-year effectiveness as well as models including the average of teacher effectiveness in the current and prior-years. In none of the cases do we find that retention patterns vary systematically with within-school differences in the math effectiveness of second- and third-year teachers.

The within-school relationship between attrition and teacher effectiveness in math is statistically significant, but is it of policy importance? We address this question using Figure 4, which shows estimated attrition probabilities for first-year teachers corresponding to Model B estimates of the effectiveness coefficients. To compute such probabilities, one also needs estimates of the school-specific constants (α_s^2 , α_s^3 and α_s^4), as Equation (2) makes clear. The probabilities shown in Figure 4 are for the case where the values of α_s^2 , α_s^3 and α_s^4 imply the estimated transition probabilities, evaluated at the mean value of E_j (i.e., zero), equal the observed transition rates. This is what would result had the α_s^h been restricted to be the same across schools (i.e., $\alpha_s^h = \alpha_s^h$ for all schools) and jointly estimated along with the efficiency coefficients.¹³ Thus, the general heights of the three curves in Figure 4 (i.e., their intercepts) are

¹³ The estimated probabilities evaluated at the means of the explanatory variables will equal the relative frequencies observed in the data used in estimation.

determined by the overall transition rates observed in the data, with the slopes of the three curves determined by the estimated effectiveness coefficients in Model B.

As shown in Figure 4, a first-year teacher whose effectiveness is one standard deviation below the mean (-0.13) has an estimated probability of transferring within NYC that is 62 percent higher than that for a teacher one standard deviation above the mean (12.8 vs. 7.9 percent). There is a 73 percent difference in the estimated probability of quitting (8.5 vs. 4.9 percent). Note that the range of teacher effectiveness values shown on the horizontal axis, -0.25 to +0.25, is slightly larger than that in going from the fifth to the 95th percentile of math value-added. The estimated probabilities of transferring within NYC and leaving the NYS system are well over twice as large at the fifth percentile of value-added compared to estimated probabilities at the 95th percentile. Less effective teachers are much more likely to transfer or leave the NYS system than are their more effective colleagues.

The analyses so far show that more effective teachers are less likely to transfer or leave teaching after their first year, but they do not provide a good measure of how much more effective, on average, teachers are who stay, relative to those who transfer or leave. Figure 5 shows the distribution of the value-added in math for first-year fourth- and fifth-grade teachers by their transition status following the first year of teaching. Consistent with the attrition patterns discussed above, two differences stand out. First, a greater proportion of teachers transferring within NYC are less effective than those who remain in the same school, as shown by the greater frequency of transferring teachers having low levels of math effectiveness, in particular values between -0.35 and -0.15. Consider the somewhat arbitrary thresholds of plus or minus one standard deviation in math effectiveness (0.13). Fifteen percent of those first-year teachers who remain in the same school were below the -0.13 threshold, compared to one quarter of those transferring within NYC. Among the most effective teachers, 17.5 percent of those who remain in the same school have effectiveness estimates that are at least one standard deviation above the mean. This contrasts to nine percent for those who transfer within NYC. The second notable difference in effectiveness is that those leaving teaching in New York State public schools are substantially less effective than their peers who remain in the same school. Two-thirds of the first-year teachers leaving the NYS system are less effective than the median for first-year teachers who remain in the same school.

As suggested by Figure 5, there are meaningful differences between teachers who leave and their peers who remain in the same school. The top row of Table 2 shows the average within-school differences in teacher effectiveness in math for fourth and fifth-grade teachers. On average, those transferring within NYC are less effective by -0.046 compared to the first-

year teachers who remain in the same schools.¹⁴ The average difference for those who leave the New York State public school system is -0.044. To put these numbers into perspective, 0.050 is the average difference in effectiveness between the second year of teaching and the first, for those individuals who remain in the same school for a second year. From a different perspective, -0.046 and -0.044 are one third as large as the standard deviation of the math value-added measure for first-year fourth- and fifth-grade teachers. By either perspective, these differences in effectiveness across retention groups are meaningful.

The analyses so far have looked at all schools together. However, as discussed above, teachers systematically sort across schools due to their own preferences and how school leaders differ in their handling of personnel matters (e.g., counseling-out ineffective teachers). Thus, it would not be surprising if the aggregate results described so far mask differences across schools, particularly schools grouped by student achievement, race/ethnicity or poverty. Model C in Table 1 explores such potential differences using interactions between the measure of effectiveness in math and dummy variables indicating whether a school is in the quartile of NYC schools having the lowest average student performance on the fourth- and fifth-grade math exam (lower-scoring school), whether the school is in the middle 50 percent of schools and whether the school is in the higher-scoring quartile. In this way, we estimate separate effectiveness coefficients for each of the three school groupings. All three of the coefficients for NYC transfers are statistically different from zero and statistically different from each other.¹⁵ That is, for each school type, greater effectiveness is associated with a lower probability of transferring, relative to staying in the same school, but the relationship between effectiveness and the probability of a NYC transfer is less strong in lower-scoring schools.

The evidence for leaving the New York State system is somewhat different. The effectiveness coefficients for leaving teaching in New York State are statistically different than zero for lower- and middle-scoring schools, implying that greater effectiveness is associated with a lower probability of leaving teaching, relative to remaining in the same school. Note that the magnitude of the estimated coefficient for lower-scoring schools is twice as large as the coefficients for middle- and higher-scoring schools, the last of which is not statistically different from zero. The hypothesis that the three coefficients are equal is rejected at the one percent level of significance, indicating that the relationship between teacher effectiveness in math and the probability of leaving teaching in NYS is relatively stronger in the lowest scoring schools.

¹⁴ These estimates and standard errors were obtained by regressing the value-added measure on dummy variables indicating the three transitions as well as school fixed effects.

¹⁵ Using a likelihood-ratio test, the hypothesis that the three coefficients are equal is rejected at the five-percent level of significance.

There does not appear to be a relationship between teachers' effectiveness and their probability of transferring to another district for any of the school types.

As shown in Figure 6a corresponding to Model C, the relationships between math effectiveness and the estimated probability of a NYC transfer are somewhat different across the three school groupings.¹⁶ In particular, the decline in the estimated probability of a NYC transfer associated with a given increase in relative effectiveness is only half as large in lower-scoring schools compared to higher-scoring schools, as indicated by the slopes of the curves. There are even larger differences across school groups in the relationship between math effectiveness and the estimated probability of leaving the NYS public system, as shown in Figure 6b. However, here the pattern is reversed. For first-year teachers in lower-performing schools, there is a 14 percentage-point reduction in the probability of leaving the NYS system as one moves from roughly the fifth to the 95th percentile in teachers' math effectiveness. In higher-scoring schools, the change is three percentage points.

As shown in Figure 2, school-level attrition rates in lower-scoring schools are substantially greater than in higher-scoring schools. Patterns seen in Figures 6a and 6b help explain this result. First, the lower-scoring schools lose relatively more of their higher-value-added math teachers, as a result of transfers within NYC. Second, they lose relatively more of their lower-value-added teachers through attrition from the NYS system. Two statistics underscore the importance of these patterns. First, among the first-year fourth- and fifth-grade teachers having relatively high math value-added, 47 percent of those switching NYC schools transfer out of schools in the lower-scoring quartile. This figure is almost twice as large as would be the case had the more effective teachers who transfer been drawn uniformly from all schools. A second statistic is less troubling. Among the fourth- and fifth-grade teachers with relatively low math value-added, 43 percent of those who leave the NYC workforce come from schools in the bottom quartile of student performance.

How do these differences in effectiveness vary by the average student performance level of the school? Table 2 shows the mean differences in effectiveness by attrition status for teachers grouped by whether the schools in which they teach during the first year are in the

¹⁶ The estimated probabilities of a NYC transfer reflected in each of the curves in Figure 6a were computed using the same strategy as that employed in computing the estimated probabilities shown in Figure 4. For example, the values of the school-specific constants for teachers in lower-scoring schools were set so that the estimated probability of a NYC transfer, evaluated at $E_j = 0$, equals the proportion of first-year teachers in these schools who actually made such transfers. Thus, the heights of the three curves reflect the rates at which teachers in the three groups of schools actually transferred within NYC. The slopes of the curves reflect the relationships between the estimated transition probabilities and teacher effectiveness implied by Model C. The same is true for the estimated probabilities in Figure 6b.

quartile of schools having lower-scoring students, the middle 50 percent of schools or the quartile of schools having higher-scoring students. The eight percent of first-year teachers in lower-scoring schools who leave the NYS system are less effective than the first-year teachers who remain in the same schools by an average of -0.070 – half as large as the standard deviation of the math value-added measure for all fourth- and fifth-grade teachers and 40 percent larger than the average gain in math effectiveness associated with having the first year of teaching experience. Less than four percent of first-year teachers in the higher-scoring schools quit after their first year; their average difference in effectiveness is smaller in magnitude (-0.028) and not statistically different from zero. The average math value-added for the fourth- and fifth-grade teachers who transfer within NYC is lower than that for their peers who remain in the same schools – for all three school groupings (-.039, -.048, and -.059 for low-, middle-, and high-scoring schools respectively). These, too, are educationally important differences.

Measures of the relative effectiveness of fourth- and fifth-grade teachers in improving the ELA scores of students are shown in the bottom panel of Table 2. Qualitatively, the pattern is similar to that for effectiveness in math but the magnitudes of the differences generally are smaller. As noted above, there is no systematic relationship between the transition probabilities and teacher ELA value-added once the math value-added of teachers is taken into account. The pattern for differences in ELA value-added in Table 2 results from the correlation between ELA and math value-added (0.47) and the systematic relationship between math value-added and the transition probabilities.

Less-effective novice teachers more likely to leave – 6th through 8th grade results. Figure 7 shows attrition rates for first- and second-year middle-school math teachers and, for comparison, gives the attrition rates for fourth- and fifth-grade teachers. The rates of NYC transfer following the first year of teaching is 60 percent higher for middle-school math teachers than for those in grades four and five (16.4 vs. 10.1). Following the second year, there is a three-fold difference in NYC transfers. Middle-school math teachers also are relatively more likely to leave the NYS system after their second year of teaching (13.0 vs. 8.8 percent). The pattern for middle-school ELA teachers is similar.

The attrition rates for middle-school math teachers are shown separately in Figure 8 for teachers in schools grouped by student performance. Middle-school math teachers in lower-scoring schools are over twice as likely to transfer to another NYC schools after the first year and four times as likely after the second year, compared to middle-school math teachers in higher-scoring schools. A comparison of Figures 2 and 8 shows that the rates at which first-

year teachers transfer within NYC are very similar for 6-8 grade math teachers and 4-5 grade teachers in middle- and higher-scoring schools. The same is not true for these two groups of teachers in lower-scoring schools. In fact, the higher transfer rates for middle school math teachers is explained entirely by the transfer rates in lower-scoring schools. Similarly, the overall higher rate at which middle-school math teachers leave the NYS system after the second year, compared to teachers in grades four and five, reflects the high quit rates for the middle-school math teachers in lower- and middle-scoring schools. Forty one percent of the first-year middle-school math teachers teaching in lower-scoring schools transfer within NYC during the first two years. With an additional 18 percent leaving the NYS public school system and modest transfers to other NYS public schools, only 38 percent of the first-year math teachers teaching in lower-scoring schools return to the same school for a third year.

We find no systematic differences in attrition for second- and third-year teachers when we estimate transition behavior employing the logit model described above; see model D in Table 1. Unlike for fourth and fifth grade teachers, the probability of middle-school math teachers making a NYC transfer, relative to that of remaining in the same school, in this model appears not to vary with teacher's relative effectiveness in teaching math – at least when all such teachers are grouped together. However, the aggregate results mask dramatic differences across school types, as shown by the parameter estimated in model E and the implied probabilities of NYC transfers in Figure 9a. In all but lower-scoring schools, the estimated probability of a NYC transfer declines as teachers are more effective; the relationship reverses in lower-scoring schools. Note that the estimated transfer probabilities (Figure 9a) are somewhat similar across the three school groups for the least effective teachers. However, the same is not true for relatively more effective teachers. Consider teachers whose math value-added is one standard deviation above the average for their school peers (0.10). Such a relatively more effective teacher in a lower-scoring school is over four times as likely to transfer within NYC compared to the teacher in a higher-scoring school (26.8 vs. 5.9 percent). An implication is that most of the more effective teachers who transfer within NYC following their first year will be leaving schools having relatively low student scores. Remarkably, 60 percent of the middle-school math teachers in the top quartile of effectiveness who left their initial school placement after the first year left schools grouped in the lower-scoring quartile

With respect to leaving the NYS system, we do not find a statistically significant relationship between teacher value-added and the probability of quitting, relative to that of remaining in the same school, for middle-school math teachers in middle- and higher-scoring schools. In contrast, the probability that a middle-school math teacher in a lower-scoring school

will leave the NYS system is lower as value-added rises (Model E and Figure 9b). The estimated probability of quitting for a teacher whose effectiveness is one standard deviation below average is three times as large as that for a teacher whose effectiveness is one standard deviation above average (14.7 vs. 4.3 percent).

The top row of Table 3 shows average within-school differences in teacher effectiveness for middle-school math teachers. On average, those who leave the NYS public system are less effective by -0.043, compared to the first-year teachers who remain in the same schools. The average difference for all those who transfer within NYC is both small and not statistically different from zero. However, schools vary significantly in this regard. In middle schools with higher-scoring students, the value-added of those who transfer within NYC is lower than that of their peers who remain in the same schools by -0.055 on average. Whereas there is no difference for those transferring out of lower-scoring schools, the first-year math teachers in these schools who leave the NYS system are less effective than their peers who remain in the same schools by -0.062. These systematic differences are quite large when compared to the 0.038 gain in effectiveness from those returning to the same school having a year of experience. From a different perspective, -0.055 and -0.062 are relatively large when compared to the 0.101 standard deviation of the value-added measure for all first-year middle-school math teachers. With more than ten percent of first-year teachers in higher-scoring schools transferring, their attrition could meaningfully improve student achievement in those schools.

In general, the attrition rates of middle-school ELA teachers by their value-added in ELA are less systematic and differences are smaller. For example, consider Model G in the bottom panel of Table 1. The pattern of estimated coefficients associated with NYC transfers is qualitatively similar to that for middle-school math teachers. However, none of the coefficients are statistically different from zero, even though the hypothesis that the three coefficients are equal is rejected at the one-percent level of significance. The positive estimate of β_2 for lower-scoring schools (1.244) is consistent with the probability of a NYC transfer increasing as the teacher's ELA value-added is higher, with the pattern reversed for schools in the other two categories. There appears to be no systematic pattern for the estimated probability of middle-school ELA teachers leaving the NYS system.

Why might the ELA value-added patterns differ from those for Math in both grade groupings? One possibility relates to a finding by Jacob and Lefgren (2005) who compare estimates of teacher's effectiveness, obtained using an approach quite similar to that we used, with subjective evaluations provided by principals. In particular, principals are asked to assess how effective teachers were "at raising student math (reading) achievement." They find that

“principals appear good at identifying those teachers who produce the largest and smallest standardized achievement gains,” and that principals are less successful at distinguishing teachers’ effective in reading, compared to math. For example, Jacob and Lefgren estimate that 69 percent of the teachers principals give the lowest rating in math actually are correctly classified. In contrast, they estimate that principals only correctly identify 42 percent of the “bottom” teachers in reading. To the extent that principals “counsel out” teachers they perceive as being less effective, a difference in their ability to distinguish effective teaching in math vs. ELA could be a factor in explaining the difference in attrition results. Alternatively, the student exams may be a better instrument for identifying teachers’ effects in math than in ELA.

The results for both grade-level groupings point to systematic differences in attrition behavior for more and less effective teachers, but they do not provide a good explanation for the differences. As noted above, the observed pattern that more effective math teachers have lower attrition rates does not establish causation. Even if it were true that lower effectiveness were a cause for higher attrition, we still would not know the mechanism through which effectiveness causes the observed actions. Do less effective teachers choose to leave their job on their own; or do they get “counseled out”; or are they subject to a more direct action taken by their employer? Separating supply and demand in the context of a teacher’s employment or transition status is very difficult.¹⁷ From this perspective, our findings regarding the difference between math and ELA effectiveness could reflect less effective teachers wanting to leave and teachers themselves being better judges of their effectiveness in math.

IV. Characterizing NYC Transfers

Less-effective teachers disproportionately leave after their first year. Some of these less-effective teachers leave teaching but others transfer to other schools. The effect that transferring has on students depends in part on the schools to which these teachers transfer. Two mechanisms come into play here. First, if the less effective teachers who transfer are systematically more likely to transfer to schools serving low-performing students, than are the more effective teachers who transfer, then the transfer process would further disadvantage schools with lower performing students. Alternatively if more effective teachers are differentially more likely to go to low-scoring schools then the transfer process can benefit the quality of teaching in those schools. Second, teachers who transfer may be more effective in the schools they transfer to than in the schools they came from. If this is the case then they may benefit the

¹⁷ For a discussion of these issues and one method to disentangle supply and demand in the context of hiring novice teachers, see Boyd et. al. (2006).

schools to which they transfer ; the transfer process would then be a net gain for both the sending and the receiving school.

Between eight and 23 percent of first-year teachers transfer to a different school following their first year of teaching, depending on grade level and academic performance of the school. To understand these transfer patterns, we compare the attributes of the schools in which they initially teach with those to which they transfer, including how such differences vary with the value-added of teachers in their first year. In so doing, we need to account for a natural tendency for teachers in low-scoring schools to move to higher-scoring schools – there are simply more higher-scoring schools to move to – and the reverse for teachers transferring from high-scoring schools. This *regression to the mean* is likely to hold for a variety of school attributes. If the effectiveness of teachers who transfer were correlated with their initial schools' attributes, such regression to the mean would complicate the interpretation of simple mean differences between the pre- and post-move schools.

We net out the effect of regression to the mean by regressing the difference in each school attribute between the pre- and post-move schools on the pre-move school attribute value where this variable is expressed as a deviation from the overall mean. A negative value for the regression coefficient associated with this variable indicates regression to the mean. The coefficients on the variables indicating the value-added category of teachers show how transfer patterns vary across these categories. The results in Table 4 show a systematic pattern. Net of regression to the mean, the less effective teachers who transfer move to schools that are very similar to their initial placements. In contrast, *the more effective teachers move to schools having higher student test scores and fewer poor, Black and Hispanic students.*

Consider the average math test scores of students in schools, a measure of school-level academic performance. On average, teachers move to schools that have math scores that are greater than the schools they left by 0.065 (column 1). However, the difference between the new and original schools differs with the first-year math value-added of teachers. Less effective teachers move to very similar schools; 0.018 in column 5 is not significantly different from zero. In contrast, more effective teachers move to schools whose scores for students are 0.104 higher on average, with the school difference being almost as big (0.081) for the middle group of teachers.

These differences are important from a policy perspective, as shown by comparing the 0.104 difference in the school average score to one or more measures characterizing the dispersion in this measure across schools. For example, consider the interquartile range for this measure. Twenty five percent of the elementary and middle schools in our sample have

average student scores that are below -0.386, with another 25 percent of the schools having average scores that exceed 0.293. The difference between the 75th and 25th percentile scores (i.e., the interquartile range), here 0.679 (= 0.293 - -0.386), is an intuitive measure of the dispersion in average scores across schools as the mean scores of half the schools fall within this range. The 0.104 average difference for the more effective teachers who move is 15 percent of the change needed to move from a school at the 25th to one at 75th percentile. The 0.104 is over one-fifth as large as the standard deviation in the school-average math score (0.482).

As a second measure of student achievement consider the percentage of students in a school whose scores are in the bottom quartile of scores citywide (i.e., the bottom 25 percent of scores) and how this measure differs between the new schools of those transferring and the schools from which they moved. After accounting for regression to the mean, teachers on average move to schools that have 2.9 percentage points fewer lower-scoring students. However, this differs with teachers' first-year effectiveness teaching math. Even though the average difference between the schools is zero for the teachers having lower value-added; teachers in the highest value-added category move to schools where the incidence of students scoring in the bottom quartile is 4.4 percentage points lower on average. This difference is approximately one-fifth of the interquartile range across schools. Table 4 also shows these same teachers move to schools with more students in the top quartile of student achievement. Among teachers transferring within NYC, those who are more effective – as measured by their contributions to the test score gains of their students in math – are more likely than their less effective colleagues from the same schools to move to schools whose students already are attaining higher academic achievement. Such systematic sorting disadvantages students in schools with high concentrations of students failing to achieve even minimal academic success.

A similar though weaker pattern emerges for schools based on student demographic characteristics. Less effective teachers on average move to schools with student race and poverty percentages that are similar to those they left. On the other hand, teachers in the middle half of the effectiveness distribution move to schools with 4.1 percentage points fewer free-lunch-eligible students and 3.5 percentage points fewer black and Hispanic students. Both of these average differences are significant and approximately one-tenth of the measures' interquartile ranges, indicating that these school differences for those transferring are more modest. The differences for the highly effective teachers are not significantly different from zero but are in the same direction as those for the teachers of average effectiveness.

So far we have seen that the more effective teachers who transfer differentially move to schools with higher scoring students. This process clearly benefits the higher performing students more than other students. However, the ultimate effect of the transfer process also depends on how well these teachers do in the schools to which they transfer. Table 5 shows that the fourth- and fifth-grade teachers who transfer have value added in their second year (first year in their new school) that is smaller than those who have taught in that same new school both years. The same is true for middle-school math teachers. These results are similar to those found in earlier work (Hanushek, Kain, O'Brien and Rivkin, 2005) and are consistent with earlier finding that transferring teachers are, on average, less effective than those who remain in the same school. Similarly, among the teachers in grades four and five who transfer, those who were relatively more effective in math in the first-year on average are relatively more effective in the schools to which they transfer; and those transferring who were relatively less effective in their first year typically are relatively less effective in their new schools. The pattern of moves is such that the second-year differences in effectiveness are roughly half as large as those in the first year.

The consistency of teachers' value-added across schools suggests that the potential mechanism that would have led to a "better fit" of teachers with their new school is unlikely to offset the differential sorting of the more effective teachers transferring into the schools with higher scoring students. In keeping with this, the bottom of Table 5 shows that in grades four and five, those teachers transferring into lower-scoring and middle group schools are less effective teaching math than are their new peers, but the same is not true for the higher scoring schools. Those transferring into higher-scoring schools are equally effective in math compared to those continuing to teach in the same schools. Middle school math teachers demonstrate a similar pattern but, again, we find no clear relationships with ELA effectiveness.

V. Summary and Conclusions

A large number of teachers leave their initial placements by the end of their first two years on the job, especially in schools with large numbers of low performing students. Our analysis in New York City schools indicates that nearly 40 percent of elementary teachers in lower-performing schools left their initial school within two years; that figure is closer to 60 percent for middle schools. For these and other reasons, teacher retention is the focus of a substantial body of recent and ongoing research and dominates many policy discussions intended to improve classroom teaching.

However, researchers and policy makers should not jump to the immediate conclusion that across-the-board reductions in teacher attrition are desirable. It may benefit students for some teachers to leave, particularly those teachers who are ineffective in improving student achievement. While we find little evidence of differential attrition by the effectiveness of teachers with more than one year of teaching experience, we find that elementary teachers and middle-school math teachers who leave teaching in New York prior to their second year are responsible for lower achievement gains for their students, on average, than are their colleagues who remain. This is particularly true for those teaching in schools where student achievement is lowest. In other words, the achievement scores of many students will likely increase as a result of the attrition of some teachers. This may be a reasonable response to a poor initial career choice and may reflect “counseling out” by school officials.

Yet, some of the problems with the attrition process relate to the pattern of transfers within New York City. Elementary teachers who transfer to other schools in New York City after their first year are less effective on average than the colleagues they leave behind. The same is true for middle-school math teachers in all but the lowest-scoring schools. That is, some ineffective teachers are leaving schools, which may be good for the students in those schools. However, these teachers are simply moving to other schools. If these less effective teachers were a “better fit” with their new schools, such transfers could result in a net gain, but we do not find evidence that this is the case. Teachers who were relatively less effective in the schools they left, on average, are relatively less effective in the schools they enter. This churning of less effective teachers occurs even though educational outcomes likely would improve if many of these individuals left teaching.

The churning could be sub-optimal even if there were no differential sorting of the teachers who transfer across schools, but this is not the case. First-year transfers who are more effective in math tend to move to schools having relatively higher student achievement and relatively fewer poor, Black and Hispanic students. Ineffective math teachers who transfer, on average, move to schools very similar in academic performance and racial/ethnic composition as those they left. Thus, the net effect is that traditionally low-performing students are further disadvantaged.

Retention policies that discriminate among teachers based on their effectiveness in improving the educational outcomes of students could be far more beneficial than indiscriminant policies aimed at reducing attrition across the board. For example, eliminating first-year teacher attrition could actually be detrimental to student achievement. Even if we assume that leavers would be replaced by first-year teachers who on average are less effective than second-year

teachers, that extra year of experience does not overcome the weak achievement gains of many of the first-year teachers who leave.

Additional policy issues arise with respect to within-district transfers. First, because a substantial number of ineffective teachers leave their first school and find jobs in another school, providing a better means to screen applicants might alter this outcome. Second, many relatively effective teachers leave their initial placements, disproportionately leaving schools with relatively more low-performing students and transferring to schools with relatively more higher-performing students, exacerbating achievement gaps. If schools with lower-performing students were as appealing to teach in as those with higher-scoring students, such sorting could be alleviated. Improving working conditions in traditionally difficult-to-staff schools is central to addressing the sorting of more effective teachers.

The results presented here raise questions about the nature of teacher retention policies. Eliminating or even reducing the achievement gap will inevitably rely on improving the quality of teachers and teaching for low-achieving, poor, Black and Hispanic students. The recruitment, selection, development, support, and retention of teachers must be linked to policies that improve outcomes for students. Several of the policy prescriptions presented here rely on having good measures of teachers' abilities to improve a broad range of outcomes for students. Unfortunately, most states and school districts do not have good measures of a broad range of student outcomes and there is well-founded concern that a focus on isolating teacher effectiveness solely employing value-added achievement results will have unintended consequences. We have much to learn about the properties of such value-added test score measures and their correlation with a broad set of student learning outcomes. Successful teacher retention policies likely will need to differentiate among the performance of teachers and create incentives to retain teachers who are most effective and either support the improvement of less-effective teachers or encourage them to leave.

Figure 1
Cumulative Attrition Rates for Entering NYC Teachers, 2000-2003

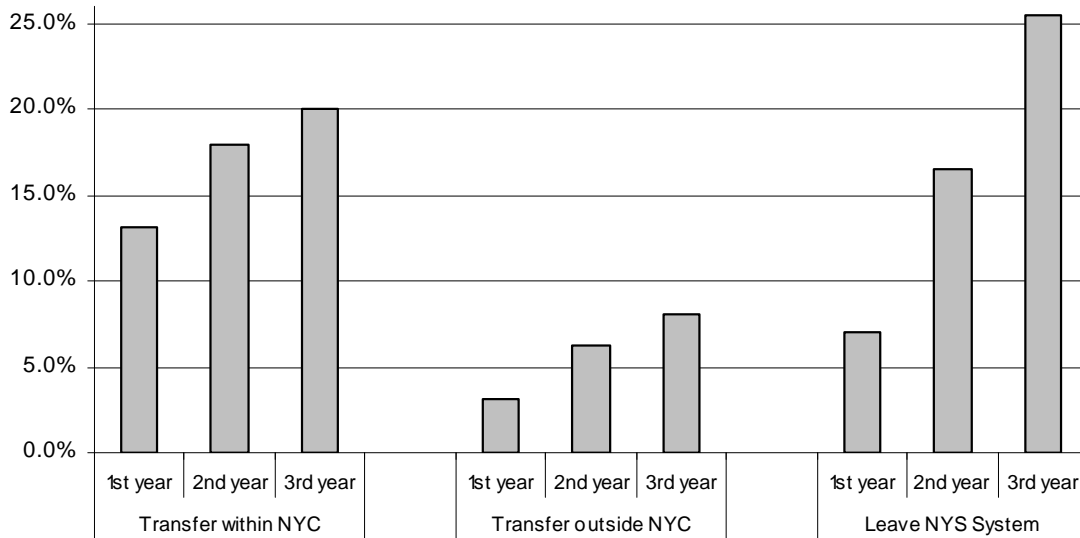


Figure 2
Attrition Rates of First- and Second-Year Teachers in Grades 4-5, by School Groupings Based on Student Performance, 2000-2005

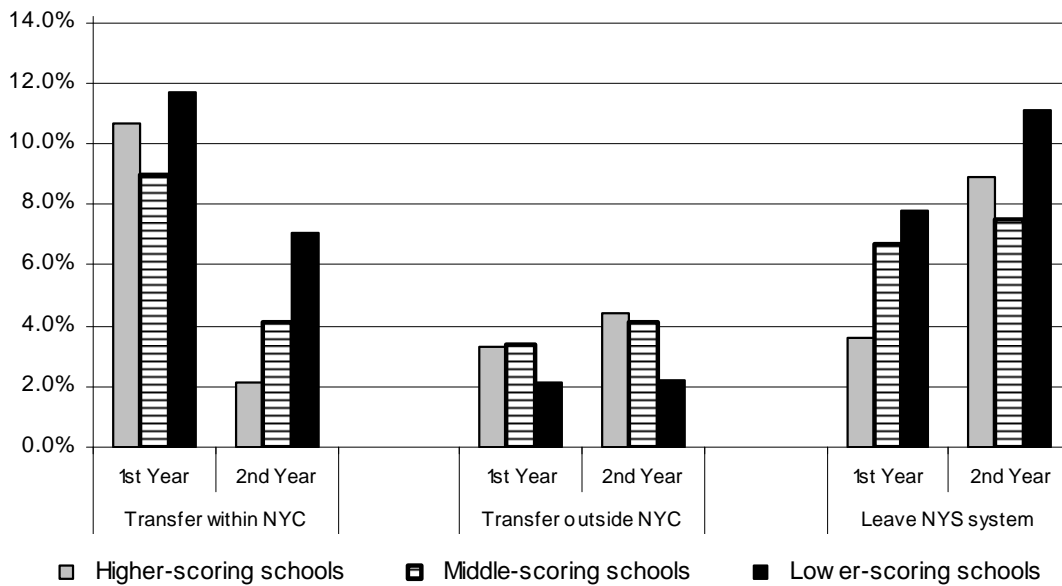


Figure 3a
Attrition Rates for First- and Second-Year Teachers in Grades 4-5,
by Groupings Based on Teachers' Value-Added in Math, 2000-2005

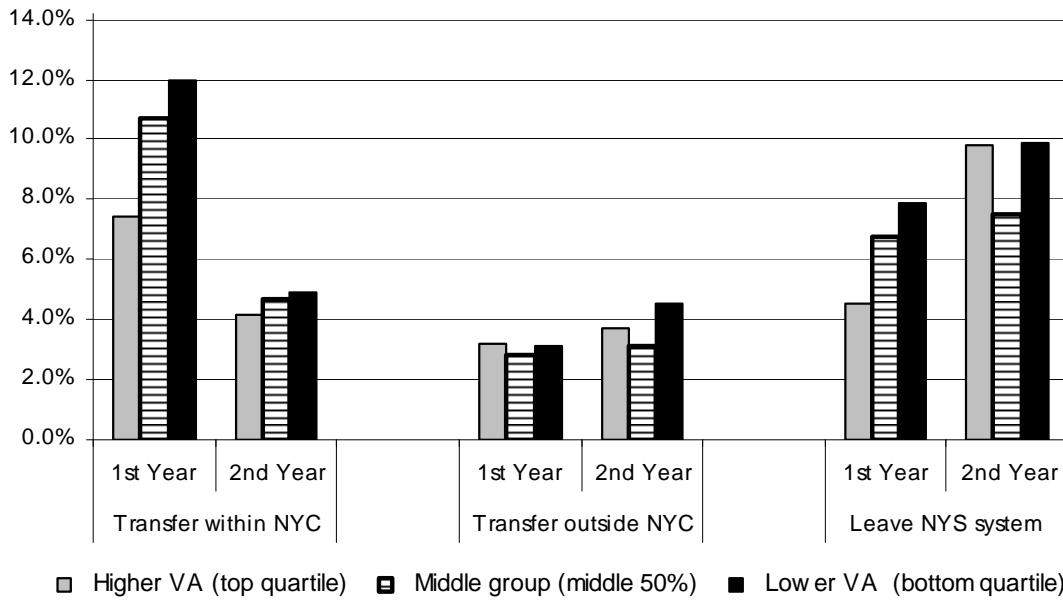


Figure 3b
Attrition Rates for First- and Second-Year Teachers in Grades 4-5,
by Groupings Based on Teachers' Value-Added in ELA, 2000-2005

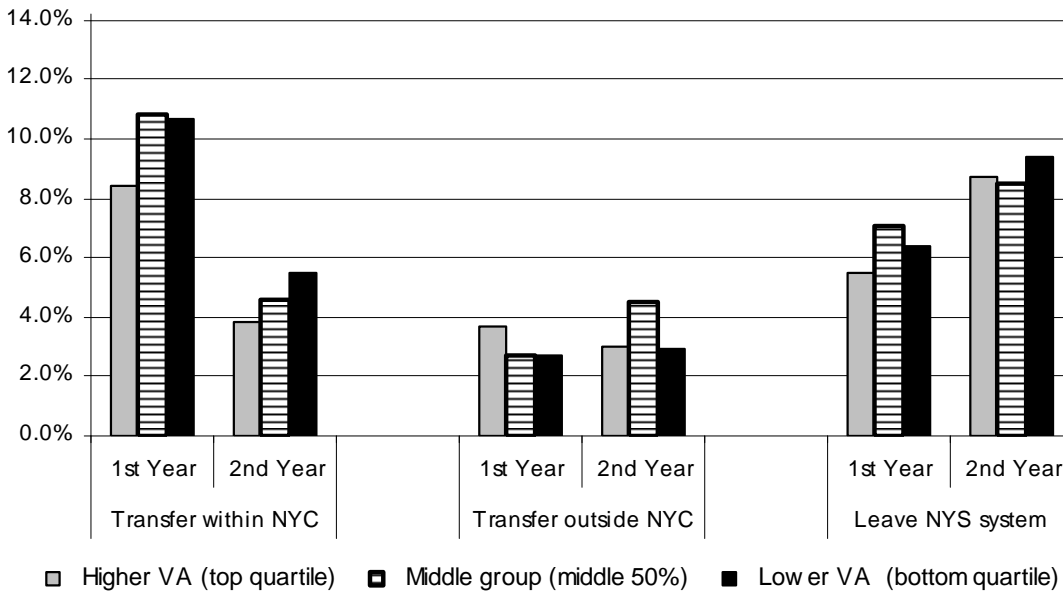


Figure 4
Estimated First-Year Transition Probabilities by Teacher's Effectiveness in Math, Grades 4-5

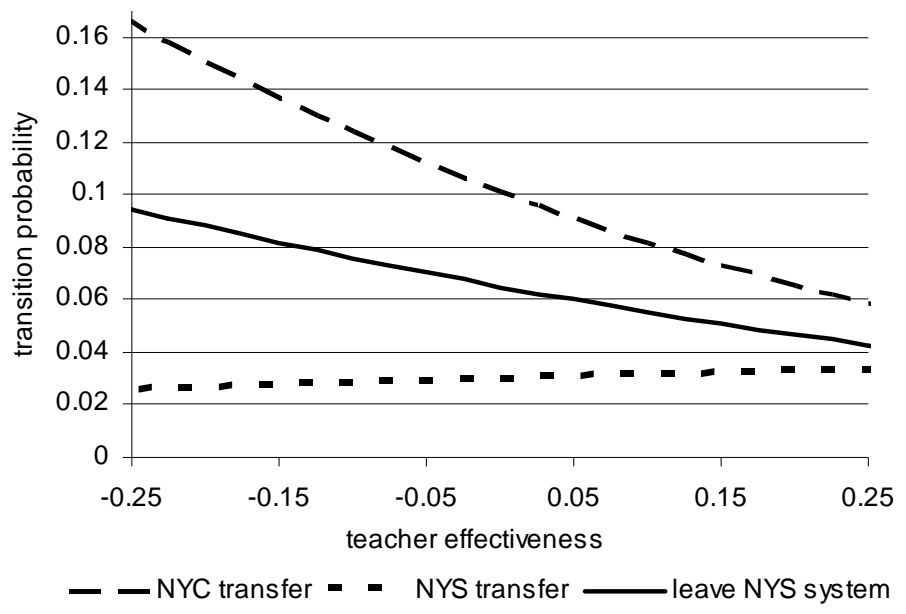


Figure 5
Distributions of Fourth- and Fifth-Grade Teacher Effectiveness in Math by Retention Status, Schools in Lower-Scoring Quartile

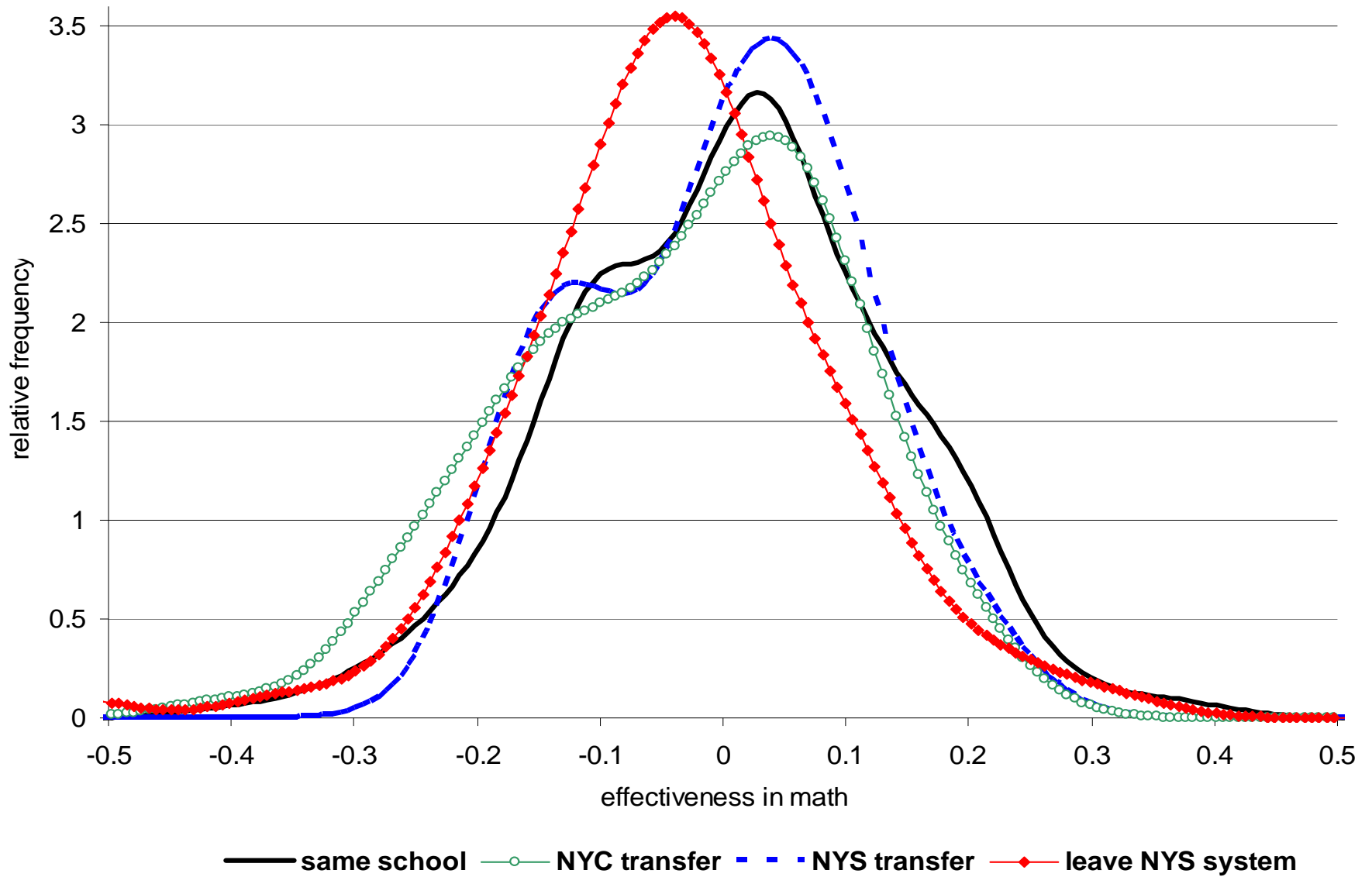


Figure 6a
 Estimated Probability of Transferring Within NYC by Teachers' Effectiveness
 in Math and School Grouping Based on Student Performance,
 First-Year Teachers in Grades 4-5

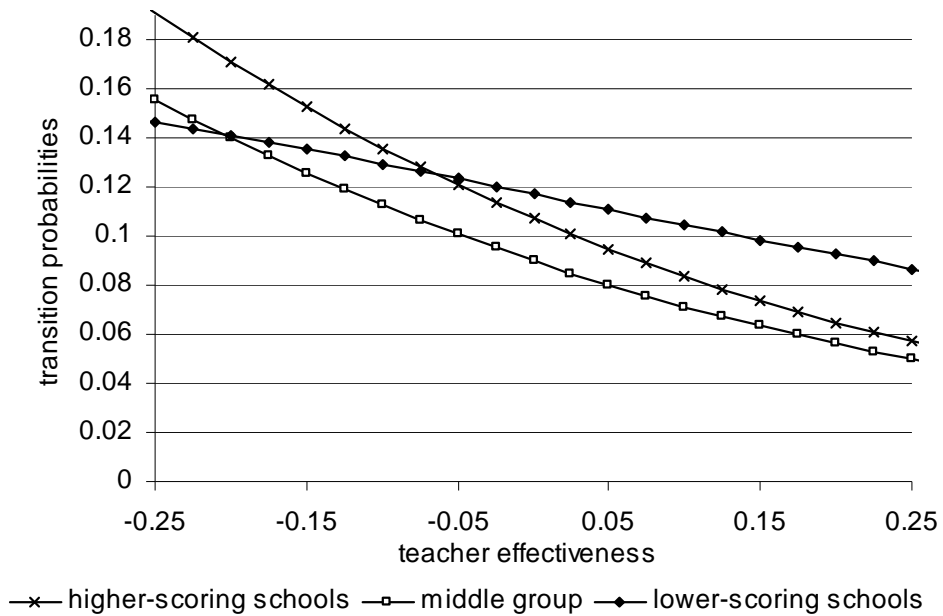


Figure 6b
 Estimated Probability of Leaving NYS System by Teachers' Effectiveness
 in Math and School Grouping, First-Year Teachers in Grades 4-5

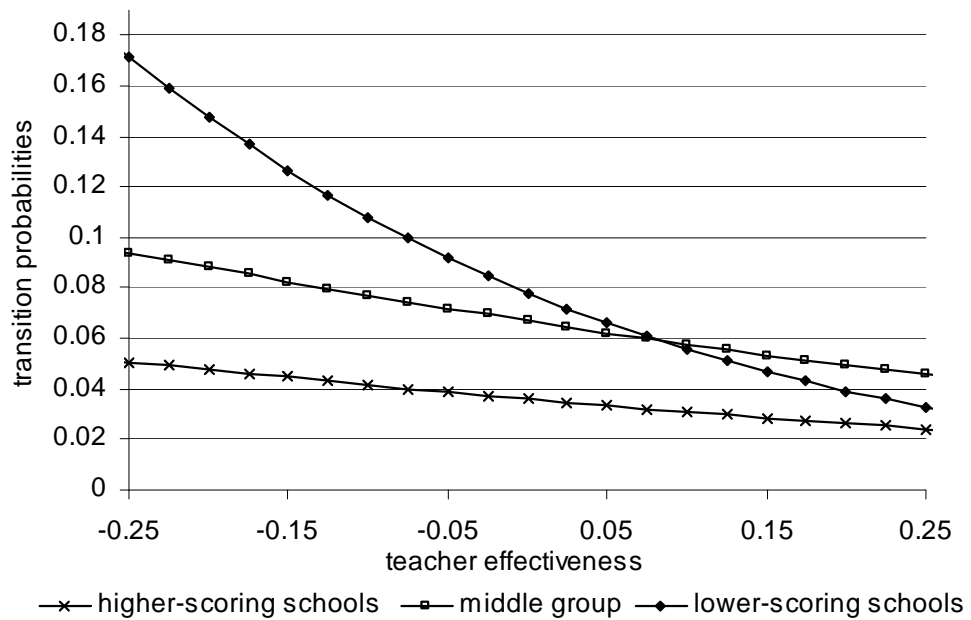


Figure 7
Annual Attrition Rates for First- and Second-Year Math Teachers in Grades 6-8

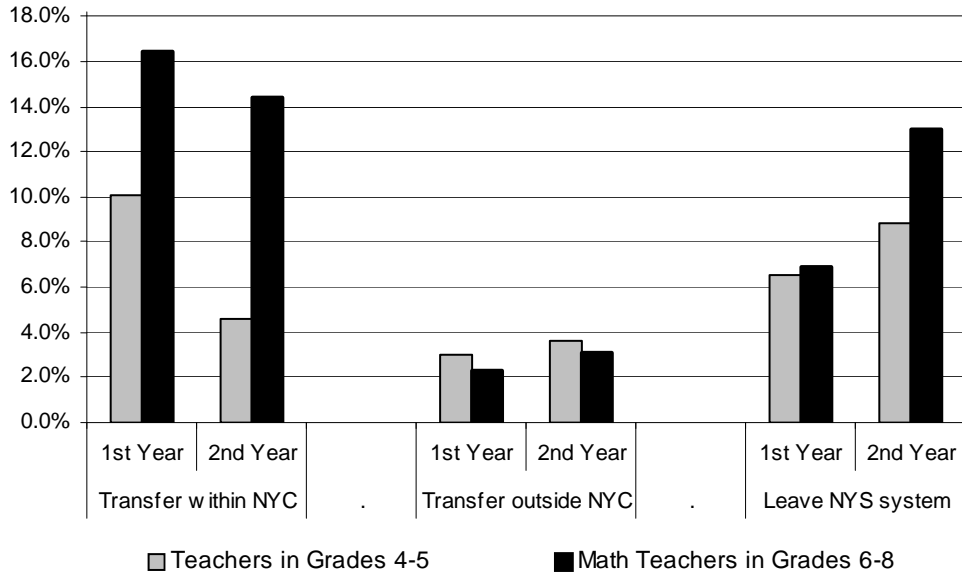


Figure 8
Attrition Rates of First- and Second-Year Math Teachers in Grades 6-8, by School Groupings Based on Student Performance, 2000-2005

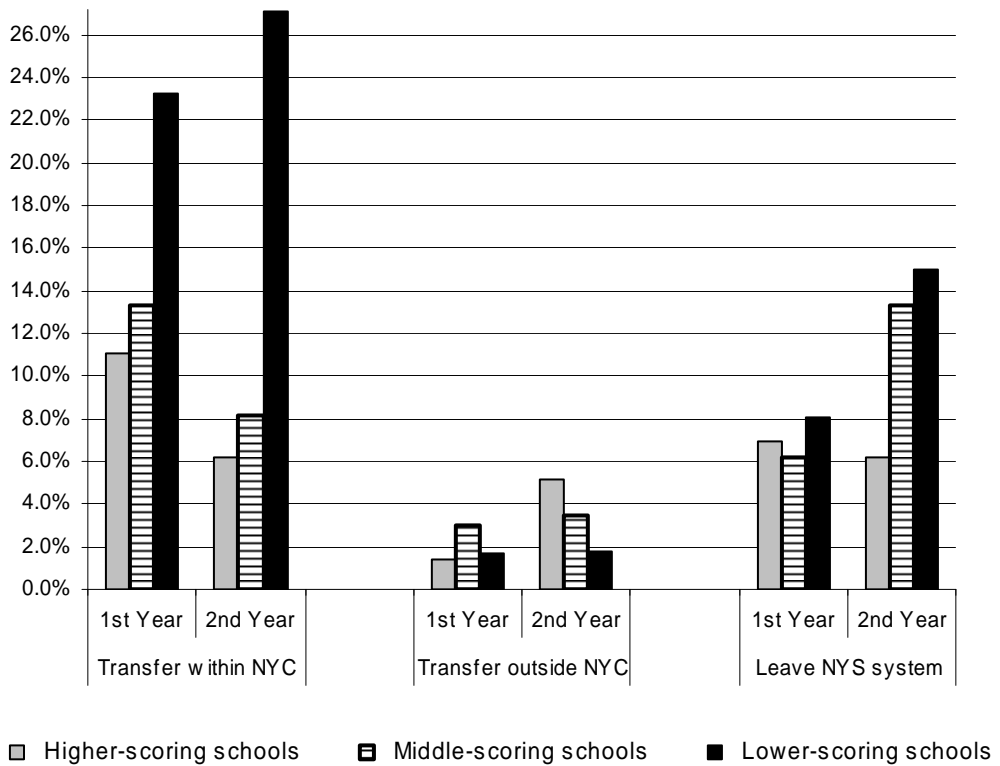


Figure 9a
 Estimated Probability of First-Year Middle School Math Teachers
 Transferring Within NYC by Math Value Added and School Grouping

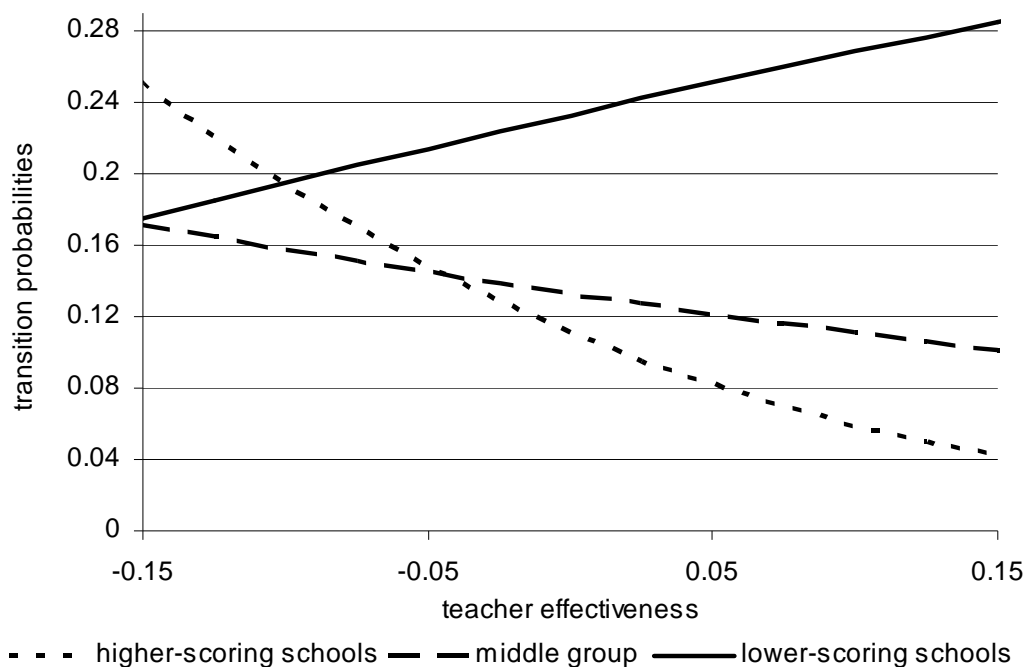


Figure 9b
 Estimated Probabilities of First-Year Middle School Math Teachers
 Leaving the NYS System by Math Value-Added and School Grouping

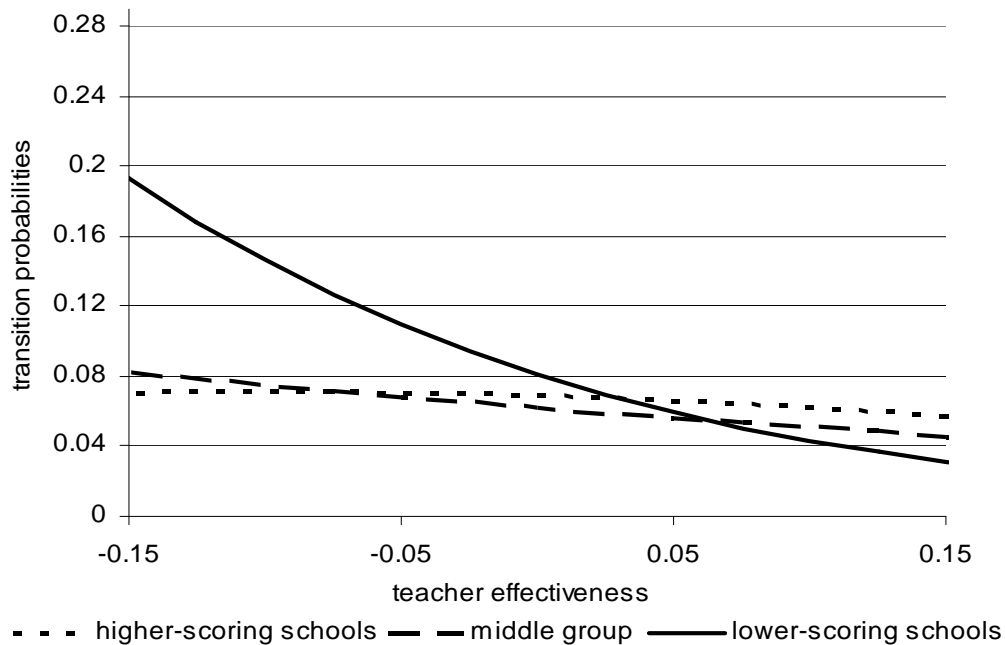


Table 1
Estimates of Parameters Reflecting How Transition Probabilities
Vary with Teacher Effectiveness, Fixed-Effect Logit Models

| Teachers in Grades 4-5 (N = 3192) | NYC transfer | | NYS transfer | | Leave NYS system | |
|--|--------------|---------|--------------|----------|------------------|---------|
| | β_2 | s.e. | β_3 | s.e. | β_4 | s.e. |
| A: Model including measures of math and ELA effectiveness, 1st – 3rd year teachers | | | | | | |
| Math effectiveness | -1.558*** | (0.431) | 0.052 | (0.677) | -1.073** | (0.424) |
| ELA effectiveness | -0.332 | (0.604) | 0.028 | (0.889) | 0.436 | (0.592) |
| B: Model entering math effectiveness separately for 2nd and 3rd year teachers | | | | | | |
| Effectiveness - 1 st year teachers | -2.231*** | (0.457) | 0.201 | (0.840) | -2.460*** | (0.558) |
| Effectiveness – 2 nd & 3 rd years teachers | -0.322 | (0.599) | -0.085 | (0.863) | 0.273 | (0.519) |
| C: Model for 1st year teachers with inter-actions for schools having lower and higher scoring students | | | | | | |
| Math effectiveness*low scoring school | -1.570** | (0.761) | -0.6940 | (2.137) | -3.823*** | (1.031) |
| Math effect. *middle group | -2.615*** | (0.664) | 0.944 | (1.160) | -1.778** | (0.803) |
| Math effect. *high scoring school | -2.839** | (1.190) | -0.924 | (2.051) | -1.906 | (1.601) |
| <hr/> | | | | | | |
| Math Teachers in Grades 6-8 (N = 1521) | NYC transfer | | NYS transfer | | Leave NYS system | |
| | β_2 | s.e. | β_3 | s.e. | β_4 | s.e. |
| D: Model entering math effectiveness separately for 2nd and 3rd year teachers | | | | | | |
| Math effectiveness - 1 st year | -0.595 | (0.709) | -0.844 | (1.930) | -3.814*** | (1.007) |
| Math effectiveness – 2 nd & 3 rd years | -0.412 | (0.964) | -1.571 | (1.841) | 0.433 | (0.974) |
| E: Model for 1st year teachers with interactions for schools having lower and higher scoring students | | | | | | |
| Math effectiveness*low scoring school | 1.320 | (0.958) | -2.316 | (3.441) | -6.401*** | (1.631) |
| Math effect. *middle group | -2.211* | (1.148) | -0.387 | (2.175) | -2.399 | (1.787) |
| Math effect. *high scoring school | -6.556** | (3.120) | 12.047 | (12.530) | -1.342 | (3.373) |
| <hr/> | | | | | | |
| ELA Teachers in Grades 6-8 (N = 1743) | NYC transfer | | NYS transfer | | Leave NYS system | |
| | β_2 | s.e. | β_3 | s.e. | β_4 | s.e. |
| F: Model entering ELA effectiveness separately for 2nd and 3rd year teachers | | | | | | |
| Effectiveness in ELA - 1 st year | -0.357 | (0.871) | 1.764 | (1.964) | -1.437 | (1.153) |
| Effectiveness in ELA - 2 nd & 3 rd years | 1.748 | (1.089) | -0.743 | (2.272) | 0.221 | (1.020) |
| G: Model for 1st year teachers with interactions for schools having lower and higher scoring students | | | | | | |
| ELA effectiveness*low scoring school | 1.244 | (1.185) | 2.269 | (3.709) | -2.626 | (1.986) |
| ELA effect. *middle group | -2.032 | (1.405) | 1.846 | (2.555) | 0.218 | (1.545) |
| ELA effect. *high scoring school | -3.210 | (3.404) | -4.035 | (8.497) | -7.337 | (4.748) |

Table 2
Average Within-School Differences in the Effectiveness of the Teachers
Making Transitions Compared to Those Remaining in the Same School and
Attrition Rates, First-Year Teachers in Grades 4-5

| | NYC Transfer | NYS Transfer | Leave NYS |
|--|----------------------|-------------------|----------------------|
| Relative Effectiveness in Math | | | |
| All Teachers | -0.046*** (0.009) | -0.007 (0.015) | -0.044*** (0.009) |
| Teachers in ... | | | |
| Lower Scoring Schools | -0.039*** (0.014) | -0.006 (0.031) | -0.070*** (0.015) |
| Middle group of schools | -0.048*** (0.013) | -0.011 (-0.02) | -0.026** (0.013) |
| Higher Scoring Schools | -0.059** (0.023) | -0.003 (0.037) | -0.028 (0.032) |
| Relative Effectiveness in English Language Arts (ELA) | | | |
| All Teachers | -0.019*** (0.007) | -0.012 (0.012) | -0.015** (0.007) |
| Teachers in ... | | | |
| Lower Scoring Schools | -0.01 (0.011) | -0.038 (0.024) | -0.028** (0.011) |
| Middle group of schools | -0.018* (0.009) | -0.001 (0.015) | -0.009 (-0.01) |
| Higher Scoring Schools | -0.037** (0.019) | -0.013 (-0.03) | 0.015 (0.026) |

Table 3
Average Within-School Differences in the Effectiveness of the Teachers
Making Transitions Compared to Those Remaining in the Same School and
Attrition Rates, First-Year Math Teachers in Grades 6-8

| | NYC Transfer | NYS Transfer | Leave NYS |
|---------------------------------------|----------------------|-------------------|-----------------------|
| Relative Effectiveness in Math | | | |
| All Teachers | -0.011 (-0.008) | 0.003 (-0.02) | -0.043*** (-0.01) |
| Teachers in ... | | | |
| Lower Scoring Schools | 0.006 (-0.013) | 0.000 (-0.045) | -0.062*** (-0.019) |
| Middle group of schools | -0.022** (-0.011) | 0.000 (-0.022) | -0.032** (-0.013) |
| Higher Scoring Schools | -0.055** (-0.026) | 0.035 (-0.064) | -0.032 (-0.026) |

Table 4
 Regression of Difference in School Attributes Between First and Second Year Teachers by
 Teacher Effectiveness in Math, Controlling for Regression Toward the Mean, Grades 4-8

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|----------------------|---------------------------------|-------------------------------|-------------------------|-------------------------------|---------------------------------|
| Change in... | All teachers | First-year value demeaned | More Effective Teachers | Middle Group | Less Effective Teachers | First-year value demeaned |
| School mean math score | 0.065*** (0.013) | -0.540*** (0.031) | 0.104***++ (0.032) | 0.081***+ (0.021) | 0.018 (0.027) | -0.509*** (0.035) |
| Percent of students scoring in bottom quartile | -0.029*** (0.005) | -0.598*** (0.033) | -0.044***++ (0.011) | -0.032***+ (0.007) | -0.011 (0.009) | -0.556*** (0.037) |
| Percent of students scoring in top quartile | 0.017*** (0.005) | -0.526*** (0.030) | 0.029**+ (0.011) | 0.024***+ (0.008) | 0.002 (0.010) | -0.510*** (0.034) |
| Percent free-lunch eligible | -0.015** (0.007) | -0.521*** (0.032) | -0.018 (0.016) | -0.041***+++ (0.011) | 0.007 (0.014) | -0.508*** (0.036) |
| Percent of students who are Black or Hispanic | -0.017** (0.008) | -0.397*** (0.030) | -0.021 (0.019) | -0.035***++ (0.013) | 0.013 (0.016) | -0.387*** (0.033) |

Table 5
 Average Within-School Differences in Teacher Effectiveness for the
 Second Year of Teaching Comparing Teachers Who Transferred Within
 NYC to Teachers in the Same Schools Who Did Not, Grades 4-8

| | Grades 4-5 | | Grades 6-8 | |
|-------------------------|---------------------|----------------------|----------------------|-------------------|
| | Math | ELA | Math | ELA |
| All Teachers | -0.035** (0.017) | -0.034*** (0.011) | -0.058*** (0.018) | -0.019 (0.015) |
| Teachers in ... | | | | |
| Lower Scoring Schools | -0.023** (0.024) | -0.026 (0.017) | -0.043 (0.029) | -0.009 (0.022) |
| Middle group of schools | -0.049** (0.023) | -0.037** (0.016) | -0.069*** (0.024) | -0.005 (0.023) |
| Higher Scoring Schools | -0.016 (0.062) | -0.049 (0.044) | -0.070 (0.066) | -0.061 (0.042) |

References

- Betts, J., K. Rueben and K. Danenberg (2000) "Equal Resources, Equal Outcomes? The Distribution of School Resources and Student Achievement in California," Public Policy Institute of California.
- Boyd, D., H. Lankford, S. Loeb, J. Rockoff and J. Wyckoff (2007) "The Narrowing Gap in New York City Teacher Qualifications and Its Implications for Student Achievement in High-Poverty Schools," working paper.
- Boyd, D., H. Lankford, S. Loeb and J. Wyckoff (2006) "Analyzing the Determinants of the Matching of Public School Teachers to Jobs: Estimating Compensating Differentials in Imperfect Labor Markets," working paper.
- Boyd, D., H. Lankford, S. Loeb and J. Wyckoff (2005) "Explaining the Short Careers of High-Achieving Teachers in Schools with Low-Performing Students," *American Economic Review Proceedings* 95(2), 166-171. An expanded version of this paper is available at www.teacherpolicyresearch.org .)
- Boyd, D., H. Lankford, S. Loeb and J. Wyckoff (forthcoming) "Do High-Stakes Tests Affect Teachers' Exit and Transfer Decisions? The Case of the 4th Grade Test in New York State," forthcoming in *Public Finance Review*.
- Chamberlain, G. (1980) "Analysis of Covariance with Qualitative Data," *Review of Economic Studies* 47, 225-238.
- Clotfelter, C., H. Ladd, J. Vigdor and J. Wheeler (2006) "High Poverty Schools and the Distribution of Teachers and Principals," Duke University working paper.
- Falch, T. and M Ronning (2005) "The Influence of Student Achievement on Teacher Turnover," CES-IFO Working Paper No. 1469.
- Goldhaber, D., B. Gross and D. Player (2007) "Are Public Schools Really Losing Their "Best"? Assessing the Career Transitions of Teachers and Their Implications for the Quality of the Teacher Workforce," working paper.
- Hanushek, E., J. Kain, D. O'Brien and S. Rivkin (2005) "The Market for Teacher Quality," NBER working paper.
- Hanushek, E., J. Kain and S. Rivkin (2004) "Why Public Schools Lose Teachers," *Journal of Human Resources* 39(2) 326-354.
- Ingersoll, R. (2001) "Teacher Turnover and Teacher Shortages: An Organizational Analysis," *American Educational Research Journal* 38(3) 499-534.
- Johnson, S (2004) "Finders and Keepers: Helping New Teachers Survive and Thrive in our Schools, The Project on The Next Generation of Teachers, San Francisco: Jossey-Bass.
- Ingersoll, R. (2004) Why do High Poverty Schools Have Difficulty Staffing Their Classrooms with Qualified Teachers? Report for Renewing Our Schools, Securing Our Future.

- Ingersoll, R. and Kralik J.M. (2004). The Impact of Mentoring on Teacher Retention: What the Research Says. *Research Review*. Education Commission of the States.
- Ingersoll, R. and T. Smith (2003). "The Wrong Solution to the Teacher Shortage." *Educational Leadership*, 60(8): 30-33.
- Ingersoll, R. and T. Smith (2004) What are the Effects of Mentoring and Induction on Beginning Teacher Turnover, *American Education Research Journal* 41(3) 681-714.
- Jacob, Brian and Lars Lefgren (2005) "Principals as Agents: Subjective Performance Measurement in Education", working paper.
- Kane, T., J. Rockoff and D. Staiger (2006) "What Does Certification Tell Us about Teacher Effectiveness? Evidence from New York City" NBER Working Paper 12155, April 2006.
- Kane, T., and D. Staiger (2002) "Volatility in School Test Scores: Implications for Test-Based Accountability Systems," in Ravitch, D. (ed.) *Brookings Papers on Education Policy 2002*, Brookings Institution, Washington, D.C.
- Lankford, H., S. Loeb and J. Wyckoff (2002) "Teacher Sorting and the Plight of Urban Schools: A Descriptive Analysis," *Educational Evaluation and Policy Analysis*, 24(1), 38-62.
- Loeb, S., L. Darling-Hammond, and J. Luczak (2005) "How Teaching Conditions Predict Teacher Turnover in California Schools," *Peabody Journal of Education*, 80(3) pp. 44-70
- Morris, C. (1983) "Parametric Empirical Bayes Inference: Theory and Application," *Journal of the American Statistical Association* 78(381) 47-55.
- Murnane, R., J. Willett, Y. Duhaldeborde, and J. Tyler (2000). "How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?" *Journal of Policy Analysis and Management* 19(4): 547-568.
- Peske, H., and K. Haycock (2006) "Teaching Inequality," The Education Trust.
- Podgursky, M. R., Monroe and D. Watson (2004) "The Academic Quality of Public School Teachers: An Analysis of Entry and Exit Behavior," *Economics of Education Review* 23(5) 507-518.
- Rivkin, S., E. Hanushek, and J. Kain (2005) "Teachers, Schools, and Academic Achievement" *Econometrica*, 73(2), 417-458.
- Rockoff, Jonah (2004). "The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data," *American Economic Review Proceedings* 94 (2): 247-252.
- Sanders, W.L. and Rivers, J.C. (1996). "Research Project Report: Cumulative and Residual Effects of Teachers on Future Student Academic Achievement," University of Tennessee Value-Added Research and Assessment Center.
- U.S. Department of Education (2007). *Teacher Attrition and Mobility: Results from the 2004–05 Teacher Follow-up Survey*.

Appendix

Value-Added Analysis: Descriptive statistics for the variables included in the four value-added models are reported in Table A1. Data for the same schools, teachers and students are used to estimate the math and ELA value-added models for fourth- and fifth-grade teachers shown as Models 1 and 2 in Table A2. However, the descriptive statistics for the class-attribute variables differ very slightly because of differences in the compositions of the classes taught by some of these teachers. Value-added Models 3 and 4 are for math and ELA in grades six through eight. The two sets of estimates are based on the same sets of schools and students, except for some missing data. However, the estimated models largely correspond to two different sets of teachers as only five percent of all math and ELA middle-school teachers teach both subjects.

Estimation of Attrition Model: The approach we used to estimate the effectiveness coefficients report in Table 1 warrants some explanation. Standard software packages such as SAS and Stata do not include procedures that allow direct estimation of the fixed-effect multinomial Logit model in (2). However, a work-around is possible since these packages can be used to estimate binary logit models containing fixed effects. Starting with our model shown in (2), consider the probability of making a particular transition, say leaving the NYS system ($h=4$), conditional on the teacher either making that change or remaining in the same school. This condition probability, shown below, is a simple binary logit probability that only depends upon the effectiveness coefficient and fixed-effect associated with this transition. Thus,

$$\tilde{P}_j^4 = \frac{\exp(\alpha_s^4 + \beta^4 E_j)}{1 + \exp(\alpha_s^4 + \beta^4 E_j)}$$

standard fixed-effect binary Logit software and data for teachers who either remain in their original school or leave the NYS system can be used to estimate β^4 . This is the method we employed for each of the three transitions, yielding estimates of all the effectiveness coefficients. The parameter estimates are consistent. However, there is some loss in efficiency compared to the case where the fixed-effect multinomial model was directly estimated.

Table A1
 Descriptive Statistics for Dependent and Explanatory Variables in Regression Models Used to Estimate Value-Added Measures for Teachers

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|-------------------------|------------------|------------------------|------------------|-------------------------|------------------|------------------------|------------------|
| | Math, Grades 4-5 | | ELA, Grades 4-5 | | Math, Grades 6-8 | | ELA, Grades 6-8 | |
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Students' own attributes | | | | | | | | |
| Math score (current year) | 0.1049 | 0.9529 | | | 0.0733 | 0.9422 | | |
| EIA score (current year) | | | 0.0725 | 0.9746 | | | 0.0433 | 0.9698 |
| Lagged ELA score | 0.0991 | 0.9342 | 0.0991 | 0.9342 | 0.0511 | 0.9508 | 0.0588 | 0.9467 |
| Lagged math score | 0.1362 | 0.9237 | 0.1363 | 0.9236 | 0.0935 | 0.9249 | 0.0994 | 0.9230 |
| School change during year | 0.1041 | 0.3054 | 0.1041 | 0.3054 | 0.4085 | 0.4915 | 0.4078 | 0.4914 |
| Female | 0.5109 | 0.4999 | 0.5109 | 0.4999 | 0.5107 | 0.4999 | 0.5106 | 0.4999 |
| Hispanic | 0.3631 | 0.4809 | 0.3631 | 0.4809 | 0.3492 | 0.4767 | 0.3445 | 0.4752 |
| Black | 0.3524 | 0.4777 | 0.3524 | 0.4777 | 0.3696 | 0.4827 | 0.3721 | 0.4834 |
| Asian | 0.1190 | 0.3238 | 0.1190 | 0.3238 | 0.1196 | 0.3245 | 0.1207 | 0.3258 |
| Other minority | 0.0048 | 0.0690 | 0.0048 | 0.0690 | 0.0034 | 0.0579 | 0.0034 | 0.0579 |
| Home Language English | 0.6143 | 0.4867 | 0.6144 | 0.4867 | 0.5884 | 0.4921 | 0.5921 | 0.4914 |
| Free-lunch eligible | 0.6656 | 0.4718 | 0.6656 | 0.4718 | 0.6256 | 0.4840 | 0.6235 | 0.4845 |
| Reduced-lunch eligible | 0.0770 | 0.2667 | 0.0770 | 0.2667 | 0.0828 | 0.2756 | 0.0832 | 0.2762 |
| Free or reduced lunch missing | 0.1130 | 0.3166 | 0.1130 | 0.3166 | 0.1563 | 0.3632 | 0.1568 | 0.3636 |
| ELL per IEP or lab exam | 0.0187 | 0.1355 | 0.0187 | 0.1355 | 0.0341 | 0.1816 | 0.0290 | 0.1678 |
| ELL per the school | 0.0001 | 0.0097 | 0.0001 | 0.0097 | 0.0001 | 0.0097 | 0.0001 | 0.0094 |
| IEP does not require bilingual services | 0.0004 | 0.0193 | 0.0004 | 0.0193 | 0.0003 | 0.0182 | 0.0003 | 0.0181 |
| Lagged absences | 10.9681 | 10.0720 | 10.9680 | 10.0719 | 12.0582 | 11.2498 | 12.0512 | 11.2492 |
| Lagged suspensions | 0.0116 | 0.1263 | 0.0116 | 0.1263 | 0.0257 | 0.1925 | 0.0257 | 0.1925 |
| Class attributes | | | | | | | | |
| Lagged ELA score - mean | 0.0979 | 0.6201 | 0.0978 | 0.6202 | 0.0500 | 0.6875 | 0.0577 | 0.6847 |
| Lagged ELA score - standard deviation | 0.6879 | 0.2009 | 0.6879 | 0.2009 | 0.6423 | 0.2045 | 0.6389 | 0.2039 |
| Lagged math score - mean | 0.1245 | 0.6015 | 0.1247 | 0.6015 | 0.0893 | 0.6667 | 0.0955 | 0.6616 |
| Lagged math score - standard deviation | 0.7052 | 0.1854 | 0.7050 | 0.1854 | 0.6333 | 0.2085 | 0.6362 | 0.2047 |
| Hispanic | 0.3639 | 0.2850 | 0.3641 | 0.2851 | 0.3459 | 0.2754 | 0.3414 | 0.2723 |
| Black | 0.3493 | 0.3318 | 0.3493 | 0.3318 | 0.3688 | 0.3199 | 0.3714 | 0.3202 |
| Asian | 0.1217 | 0.1837 | 0.1215 | 0.1836 | 0.1222 | 0.1729 | 0.1231 | 0.1730 |
| Other minority | 0.0050 | 0.0158 | 0.0050 | 0.0158 | 0.0037 | 0.0130 | 0.0037 | 0.0130 |
| Home language English | 0.6028 | 0.2791 | 0.6028 | 0.2792 | 0.5849 | 0.2612 | 0.5887 | 0.2585 |
| Free-lunch eligible | 0.6639 | 0.2961 | 0.6646 | 0.2964 | 0.6209 | 0.2889 | 0.6195 | 0.2891 |
| Reduce-lunch eligible | 0.0756 | 0.0812 | 0.0757 | 0.0813 | 0.0819 | 0.0822 | 0.0824 | 0.0823 |
| ELL per IPE or lab exam | 0.0440 | 0.0986 | 0.0440 | 0.0988 | 0.0452 | 0.1228 | 0.0397 | 0.1060 |
| Lagged absences | 11.2130 | 3.9005 | 11.2087 | 3.8983 | 12.5491 | 4.9198 | 12.5417 | 4.9287 |
| Lagged suspensions | 0.0123 | 0.0356 | 0.0123 | 0.0355 | 0.0279 | 0.0621 | 0.0279 | 0.0623 |
| Class-size | 26.3 | 4.6 | 26.2 | 4.6 | 27.3 | 5.1 | 27.3 | 5.2 |
| Grade 5 | 0.5030 | 0.5000 | 0.5030 | 0.5000 | | | | |
| Grade 7 | | | | | 0.3477 | 0.4763 | 0.3482 | 0.4764 |
| Grade 8 | | | | | 0.3260 | 0.4688 | 0.3275 | 0.4693 |

Table A2
 Parameter Estimates for Regression Models Used to Estimate Value-Added Measures for Teachers

| Dependent variable | Math Score, Grades 4-5 | | ELA Score, Grades 4-5 | | Math Score, Grades 6-8 | | ELA Score, Grades 6-8 | |
|---|------------------------|------------|-----------------------|------------|------------------------|------------|-----------------------|------------|
| | Coefficients | Std. error | Coefficients | Std. error | Coefficients | Std. error | Coefficients | Std. error |
| Student's own attributes | | | | | | | | |
| Lagged ELA Score | 0.1523*** | (0.0010) | 0.4940*** | (0.0011) | 0.1256*** | (0.0010) | 0.4753*** | (0.0011) |
| Lagged ELA Score squared | 0.0081*** | (0.0004) | -0.0131*** | (0.0004) | -0.0013*** | (0.0003) | -0.0034*** | (0.0004) |
| Lagged math Score | 0.6150*** | (0.0010) | 0.2610*** | (0.0012) | 0.5427*** | (0.0010) | 0.1850*** | (0.0011) |
| lagged math Score squared | -0.0415*** | (0.0004) | -0.0078*** | (0.0004) | 0.0004 | (0.0003) | 0.0069*** | (0.0004) |
| School change during year | -0.0037 | (0.0025) | 0.0003 | (0.0027) | -0.0370*** | (0.0027) | -0.0438*** | (0.0031) |
| Female | -0.0564*** | (0.0012) | 0.0669*** | (0.0013) | -0.0234*** | (0.0012) | 0.1038*** | (0.0014) |
| Hispanic | -0.0611*** | (0.0025) | -0.0470*** | (0.0028) | -0.0558*** | (0.0025) | -0.0355*** | (0.0028) |
| Black | -0.0889*** | (0.0027) | -0.0497*** | (0.0030) | -0.0636*** | (0.0026) | -0.0456*** | (0.0029) |
| Asian | 0.1333*** | (0.0028) | 0.0138*** | (0.0031) | 0.1120*** | (0.0028) | -0.0063** | (0.0031) |
| Other minority | -0.0581*** | (0.0093) | -0.0397*** | (0.0102) | -0.0237** | (0.0112) | -0.0494*** | (0.0124) |
| Home Language English | -0.0740*** | (0.0017) | -0.0118*** | (0.0019) | -0.0578*** | (0.0017) | 0.0013 | (0.0019) |
| Free-lunch eligible | -0.0482*** | (0.0023) | -0.0805*** | (0.0025) | -0.0266*** | (0.0022) | -0.0603*** | (0.0025) |
| Reduced-lunch eligible | -0.0210*** | (0.0029) | -0.0517*** | (0.0032) | -0.0061** | (0.0029) | -0.0313*** | (0.0032) |
| Free or reduced lunch missing | -0.0357*** | (0.0036) | -0.0377*** | (0.0039) | -0.0342*** | (0.0029) | -0.0404*** | (0.0032) |
| ELL per IEP or lab exam | -0.0854*** | (0.0055) | -0.1559*** | (0.0060) | -0.0908*** | (0.0045) | -0.1822*** | (0.0051) |
| ELL per the school | -0.0219 | (0.0652) | 0.0933 | (0.0713) | -0.0383 | (0.0651) | 0.0636 | (0.0746) |
| IEP does not require bilingual services | -0.0565* | (0.0325) | -0.0105 | (0.0356) | -0.1549*** | (0.0344) | -0.1171*** | (0.0386) |
| Lagged absences | -0.0030*** | (6.7103) | -0.0006*** | (0.0000) | -0.0040*** | (0.0000) | -0.0007*** | (0.0000) |
| Lagged suspensions | -0.0165*** | (0.0050) | -0.0276*** | (0.0055) | -0.0386*** | (0.0034) | -0.0273*** | (0.0038) |
| Class attributes | | | | | | | | |
| Lagged ELA score - mean | -0.0007 | (0.0396) | -0.1386*** | (0.0436) | 0.0770*** | (0.0041) | 0.1213*** | (0.0048) |
| Lagged ELA score - standard deviation | 0.0223 | (0.0436) | -0.0044 | (0.0480) | 0.0145*** | (0.0048) | 0.0247*** | (0.0056) |
| Lagged math score - mean | -0.2044*** | (0.0374) | 0.1465*** | (0.0412) | 0.1508*** | (0.0045) | 0.1582*** | (0.0053) |
| Lagged math score - standard deviation | 0.0607 | (0.0481) | 0.1113** | (0.0529) | 0.0570*** | (0.0046) | 0.0489*** | (0.0054) |
| Hispanic | -0.5853*** | (0.1325) | -0.2807* | (0.1452) | -0.1078*** | (0.0135) | -0.0636*** | (0.0155) |
| Black | -0.7616*** | (0.1361) | -0.5061*** | (0.1495) | -0.0941*** | (0.0133) | -0.0734*** | (0.0154) |
| Asian | -0.4151** | (0.2063) | -0.0192 | (0.2266) | 0.0370** | (0.0145) | 0.0790*** | (0.0168) |
| Other minority | -1.7313*** | (0.5047) | -1.6778*** | (0.5547) | -0.0387 | (0.0682) | -0.0664 | (0.0795) |
| Home language English | 0.2704** | (0.1110) | 0.3280*** | (0.1211) | -0.0338*** | (0.0102) | 0.0147 | (0.0118) |
| Free-lunch eligible | -0.2335** | (0.1108) | -0.1182 | (0.1233) | -0.0687*** | (0.0094) | -0.0881*** | (0.0108) |
| Reduce-lunch eligible | -0.1555 | (0.1745) | -0.6203*** | (0.1938) | -0.0102 | (0.0153) | -0.0725*** | (0.0175) |
| ELL per IPE or lab exam | -0.2195 | (0.1494) | -0.7024*** | (0.1689) | 0.0876*** | (0.0119) | 0.0645*** | (0.0148) |
| Lagged absences | 0.0031 | (0.0036) | -0.0063 | (0.0039) | -0.0056*** | (0.0003) | -0.0047*** | (0.0003) |
| Lagged suspensions | 0.0250 | (0.2713) | 0.1825 | (0.2970) | -0.1016*** | (0.0180) | -0.1139*** | (0.0208) |
| Class-size | -0.0042* | (0.0025) | -0.0122*** | (0.0027) | 0.0000 | (0.0002) | 0.0012*** | (0.0002) |
| Grade 5 | 0.0468*** | (0.0181) | 0.2198*** | (0.0199) | | | | |
| Grade 7 | | | | | 0.0627*** | (0.0049) | 0.0488*** | (0.0060) |
| Grade 8 | | | | | 0.0232*** | (0.0056) | 0.0182*** | (0.0068) |