The Role of Teacher Quality in Retention and Hiring: Using Applications-to-Transfer to Uncover Preferences of Teachers and Schools

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Abstract
Many large urban school districts are rethinking their personnel management strategies, often giving increased control to schools in the hiring of teachers, reducing, for example, the importance of seniority. If school hiring authorities are able to make good decisions about whom to hire, these reforms have the potential to benefit schools and students. Prior research on teacher transfers uses career history data, identifying the school in which a teacher teaches in each year. When such data are used to see which teachers transfer, it is unclear the extent to which the patterns are driven by teacher preferences or school preferences, because the matching of teachers to schools is a two-sided choice. This study uses applications-to-transfer data to examine separately which teachers apply for transfer and which get hired and, in so doing, differentiates teacher from school preferences. Holding all else equal, we find that teachers with better pre-service qualifications (certification exam scores, college competitiveness) are more likely to apply for transfer, while teachers whose students demonstrate higher achievement growth are less likely. On the other hand, schools prefer to hire "higher quality" teachers across measures that signal quality. The results suggest that not only do more effective teachers prefer to stay in their schools but that schools are able to identify and hire the best candidates when given the opportunity.

INTRODUCTION

Current education policy discussions often focus on the importance of teachers and the need to improve teacher quality. In order to achieve and maintain a strong workforce, schools need to attract high-quality teachers, select the best teachers from the pool of candidates available, and retain those teachers who are particularly effective. The current research literature describes the career paths of teachers and how those vary by teacher quality (see Boyd et al., 2005; Hanushek et al., 2005; and Goldhaber, Gross, & Player, 2007 for examples). However, this research does not distinguish between the preferences of teachers and those of employers. Do higher quality teachers seek to leave schools? Do schools select high-quality candidates from the pool of teachers interested in their positions? How do these relationships differ across different dimensions of quality and across teachers in different types of schools? This paper sheds light on these questions by examining teachers' applications to transfer, which allow the separation of teachers' decisions to apply from schools' decisions to hire. Understanding the role of teachers in comparison to the role of school hiring authorities in determining the sorting of teachers across schools allows policymakers both to more effectively target the causes of the disparities in the teacher workforce across schools and to better predict the effects of new policies such as those that give schools greater flexibility in hiring.

Teacher quality is an imprecise concept. At times, research and policy discussions use proxies for teacher quality based on teachers' pre-service qualifications such as certification status, teachers' own test performance, or the characteristics of their college or graduate education. At other times, researchers and policymakers proxy teacher quality by using practice-based measures such as teaching experience or the test performance gains of students, often referred to as teachers' value-added to student achievement. Studies show that teachers with higher pre-service qualifications are typically more likely to transfer across schools and leave teaching altogether (Boyd et al., 2005; Goldhaber, Gross, & Player, 2007). Boyd et al. (2005) find that this relationship is especially strong in low-achieving schools. On the other hand, research on practice-based measures, such as teacher experience and value-added to student achievement scores, demonstrate the opposite result. Experienced teachers are less likely to leave schools than are their less experienced peers (Ingersoll & Smith, 2003; Marvel et al., 2007); and more effective teachers are less likely to transfer and leave the profession than are less effective teachers (Boyd et al., 2007; Hanushek et al., 2005; Goldhaber, Gross, & Player, 2007). For example, Goldhaber, Gross, and Player (2007) find that the most effective teachers remain in teaching and in the same school for the longest period of time.[i] Moreover, this holds true for effective teachers at both low and high achieving schools.

Prior studies of teacher turnover have depended upon career history data to estimate teachers' preferences for specific schools and features of schools. The drawback of this approach is that career moves, particularly transfers across schools, are not driven solely by teachers' choices. The choices of school hiring authorities as well as the requirements of institutional structures and policies, such as seniority transfer rights, can mask the relationship between teachers' preferences and job changes.[ii] Work history data can tell us when movement occurs but does not capture the joint nature of hiring decisions—where both a teacher's decision to apply for transfer and a school's decision to hire that teacher determine the final matching. We do not know, for example, whether teachers with higher pre-service qualifications are more likely to transfer because they are in higher demand or because they are more likely to seek transfer in the first place. Likewise, we are unsure whether more effective teachers, as measured by student test score gains, tend to stay because they prefer their current settings or because their effectiveness is not currently rewarded in school hiring practices.

This study begins to untangle supply from demand characteristics in teacher transfer by focusing on applications-to-transfer data files that provide a unique view into the teacher labor market. Examining which teachers apply for transfer sheds light on teacher preferences. At the same time, the data include information on which applicants are selected for hire and which are not, which can be used to estimate school preferences for teachers. Two substantive questions guide our study: Which teachers are more likely to request transfers? What kinds of teachers do schools choose to hire? Additionally, we ask the methodological question: What do we learn from applications data that we would not have learned from work history files alone?

Change in New York City Transfer Request System

This study draws on data from an open-market system for New York City (NYC) teachers to apply for transfer. In 2005, the Department of Education and its teachers union decided to reform prior hiring policies to move away from a system that was based on seniority and gave teachers and principals little input in hiring decisions to a more free-market approach. Previously, teachers applied for and received transfers through the central Human Resources or district offices, "a behind the scenes process that many teachers and schools found inscrutable" (Daly et al., 2008, p. 14). Human Resources staff assigned new placements to "excessed" teachers—who had been displaced from their jobs for any number of reasons, such as school closure or changing enrollment—often without teacher or principal input. The new policy requires that all teachers seeking transfer—both voluntary and involuntary—enter an open applications system where hiring decisions are made mutually by teacher and principal. Senior teachers can no longer claim the positions of novice teachers due to seniority, a practice that that previously tied the hands of principals in the hiring process. To achieve these objectives, the district instituted a more centralized hiring system, including an online infrastructure for searching job postings and applying to them directly. The open market system allows for transfers during a window that begins the last week in April and closes the first week in August. Transfers that occur outside of this period are not subject to the open market process and all hiring occurs from the teachers who had been excessed and had not found jobs.

Expanding the Signals of Teacher Quality

The two dimensions of teacher quality measurement discussed so far—pre-service qualifications and practice-based measures—are incomplete characterizations of quality. While we cannot hope to capture the full complexity of teacher quality, we do explore two additional characteristics of teachers that schools may consider in their estimations of teacher quality during hiring decisions—preparation pathway and race or ethnicity. A teacher's pathway into teaching may proxy for better preparation or better recruitment and selection. And, given the over-representation of white teachers relative to student demographics, schools may view recruiting a more racially diverse teaching force as a means for improving the overall ability of its staff and program to serve students. Some evidence also supports the possibility that black teachers can be particularly effective for black students (Dee, 2004).

Teacher turnover does vary by teacher preparation pathway. Overall, teachers with regular or standard certification types are less likely to move schools or leave teaching than teachers with provisional certification, and teachers from alternative routes are more likely to leave teaching and to transfer across schools than teachers from traditional routes (Marvel et al., 2001; Fisk, Prowda, & Beaudin, 2001; Fowler, 2003). Most relevant to our work, Boyd et al. (2006) find significant variation by pathway in NYC teacher attrition. Compared to college-recommending or traditional route teachers, Grossman et al. (2006) report that substantially fewer Teaching Fellows and Teach for America (TFA) teachers—the two largest alternative pathways serving NYC—left teaching after the first year. By the end of the 4th year, college-recommending teachers were much less likely to have left the profession (44.6 percent) than teachers from the Teaching Fellows program (54.7 percent), who in turn experienced much lower attrition than TFA teachers (81.3 percent). The higher likelihood among TFA teachers to remain in teaching after the first year and to leave after the second year likely reflects the programmatic expectation to commit to 2 years of teaching.

Teacher turnover also varies by teacher race and ethnicity. Using national averages, Marvel et al. (2001) report that white teachers (83.9 percent) are more likely to stay in the same school than black (79.3 percent) or Hispanic (80.6 percent) teachers. About 10 percent of Hispanic and black teachers migrate schools as compared to about 8 percent of white teachers. Black teachers are the most likely to leave the profession altogether. However, national average statistics may mask important differences in variation by teacher race or ethnicity because they do not account for differential sorting into and out of certain kinds of schools or districts, nor do they account for other teacher characteristics that may be associated with race or ethnicity. For example, migration and attrition rates that appear to vary by teacher race or ethnicity may simply reflect that teachers of different race and ethnicity tend to teach at different types of schools. Among studies that control for school, district, and other teacher characteristics, white teachers generally are less likely to stay in a school from year to year than are non-white teachers (Ingersoll, 2001; Kirby, Berends, & Naftel, 1999; Murnane et al., 1991). Boyd et al. (2005) and Hanushek, Kain, and Rivkin (2004) also find significant interactions between teacher race and racial composition of the student body in predicting the probability of transferring within NYC schools. Namely, white and Hispanic teachers are more likely to leave schools with increasing proportions of black students and decreasing proportions of white students, while there is no significant relationship between retention and student racial composition for black teachers.

DATA

NYC Administrative Data

The primary data for this paper come from the New York City Department of Education Transfer Request System. The data include applications for open positions for the 2006–2007 and 2007–2008 academic years. Each application identifies the teacher as well as characteristics of the open positions such as the school and the subject area. The data also indicate which applicants were hired for a given position.[iii]

To this data, we have linked an array of additional data on teachers and schools in the New York City School District. Data on teacher characteristics include demographic information (race, gender, age), information on professional preparation pathway, and measures for teacher quality—including years of experience and pre-service qualifications (LAST teacher certification exam score and whether teachers attended a competitive undergraduate college). Additionally, we have used student achievement data for a subset of teachers in our study to estimate their effectiveness by calculating teachers' value-added to student achievement scores (described in more detail below). Data on schools include school level (elementary, middle, high school, or "other" grade combination), student race and ethnicity, student eligibility for free or reduced-price lunch, student English learner status, when the schools was established, the experience of teachers in the school, school enrollment, crime rates, and a host of other variables.[iv]

Teachers

Table 1 presents summary statistics on characteristics of the 80,898 active teachers in our sample.[v] About 13 percent of teachers became appliers at least once over 2 years; of those who became appliers, 42 percent successfully transferred through the Transfer Request System at least one time over 2 years.[vi] Of all active teachers in NYC, three quarters were female and 62 percent were white. On average, teachers were about 41 years old with 7.5 years of experience. Most had initially entered teaching through college-recommending (traditional) routes (43 percent).

Table 1 demonstrates also that teachers who applied for transfer differed somewhat from the overall population of active teachers. Appliers were less likely to be female and white, were less experienced, a bit younger, and less likely to come from a college-recommending teacher preparation pathway. Those who entered teaching through the Teaching Fellows program, in particular, made up a relatively high proportion of appliers. Compared to all who applied for transfer, those who were successful (movers) were less likely to be white and were younger. They were also slightly less experienced, but had higher LAST certification exam scores and were more likely to come from colleges ranked as competitive by Barron's ratings. Compared to teachers who initially entered the profession with a temporary license, Teaching Fellows made up a lower concentration of active teachers and appliers in NYC, but a higher concentration of movers.[vii]

By examining whether active teachers are in a different placement in 2007–2008 than they are in 2006–2007 according to work history files, we can estimate the total number of movers and compare this number to the Transfer Request System data.[viii] As described earlier, the Transfer Request System is in place only from April until August. Because schools need to fill vacancies throughout the year, transfer hires that occur outside of the system draw from the pool of excessed teachers who had not previously found work. Approximately half of all migration of NYC teachers occurred within the Transfer Request System. Given that they had previously been excessed and were unable to find jobs while the open-market Transfer Request System was active, those who migrated outside the Transfer Request System likely differ from those who migrated within it. To assess this, we used multivariate, logistic regression to model whether migrating teachers used the Transfer Request System as a function of teacher characteristics.[ix] Those who migrated through the Transfer Request System were more likely to be younger, less experienced, Hispanic, from a selective college, have higher certification exam scores, and have entered teaching through the Teaching Fellows program. Most schools received transfers from both inside and outside of the Transfer Request System.

Teacher Quality

Our analyses include three dimensions and six measures of teacher quality:

1. Pre-service Quality Measures (Qualifications)
    a. Whether a teacher attended a competitive college
    b. Teacher Certification (LAST) exam score
2. Practice-Based Quality Measures
    a. Teacher experience (in years)
    b. Teacher effectiveness: value-added to student achievement scores
3. Additional Signals
    a. Teacher race and ethnicity
    b. Pathway into teaching

About 33 percent of teachers in our sample graduated from colleges rated in the top two out of four tiers of competitiveness according to Barron's ratings. As part of their NYC certification requirements, teachers had to take the Liberal Arts and Sciences Test (LAST) intended to measure "knowledge and skills in the liberal arts and sciences, in teaching theory and practice, and in the content area of the candidate's field of certification" (New York State Teacher Certification Examinations, 2009). The exam includes a multiple-choice section covering scientific, mathematical, and technological processes; historical and social scientific awareness; artistic expression and humanities; communication and research skills; and written analysis and expression. There is also a written component requiring teachers to prepare a response to an assigned topic. Teachers had an average score on the LAST exam of 248 (s.d. = 30).

Regarding practice-based measures, teachers average approximately 7.5 years of teaching experience. Over a third of teachers (36 percent) have 3 or fewer years of experience; slightly under a third (32 percent) have more than 10 years of experience. In terms of teachers' value-added to student achievement, we modeled student achievement in math[x] as a function of student fixed-effects, student time-varying characteristics, classroom characteristics, school characteristics, grade and year fixed-effects, and teacher fixed-effects.[xi] Because math is tested only in grades 3 through 8 and not all teachers teach math, we only have value-added scores for a subset of teachers (n = 13,223). Teachers in this study have a mean value-added score of -0.33 (s.d. = 0.24) with a minimum score of -2.5 and a maximum of +1.1.[xii] The time-varying student characteristics in the models include prior math and English language arts scores (both linear and squared), whether they changed schools that year, whether their home language is English, whether they are eligible for free lunch, whether they are eligible for reduced-price lunch, whether they are English language learners, their prior-year absences, and their prior year suspensions. The classroom-level controls include the percent of Hispanic students, black students, Asian students, other non-white students, English language learners, students whose home language is English, free lunch eligible students, and reduced-priced lunch eligible students. They also include class size, the standard deviations of lagged math and lagged English language arts scores, and the averages for lagged absences, lagged suspensions, lagged math scores, and lagged English language arts scores. The school-level controls include enrollment, the percentage of black students, the percentage of Hispanic students, the percentage of free lunch students, the percentage of English language learners, and the expenditure per pupil.

Sixty-two percent of active teachers in our sample are non-Hispanic whites, with another 19 percent black and 13 percent Hispanic. Approximately 43 percent of teachers in the district entered teaching through traditional, college-recommending pathways, while others entered through alternative, early-entry routes such as the New York City Teaching Fellows (12 percent) and Teach for America (2 percent). Many teachers entered without initial certification, through temporary licensure (22 percent).

Schools

The teachers in our sample teach at 1366 different schools, over one half of which are elementary schools, about one fourth are high schools, one fifth are middle schools, and less than 1 percent fall outside of these designations ("other").[xiii] Table 2 describes the schools. On average, over three -fourths of students in NYC schools are either Hispanic or black, with a slightly higher concentration of Hispanic than black students overall. About 70 percent of students qualify for free or reduced school lunch and almost 15 percent of students scored in the lowest-level on their math achievement exam.

There is descriptive evidence for teacher sorting by quality indicators into schools serving different student demographics. Table 3 shows that black teachers teach in schools with the highest concentration of black students while Hispanic teachers teach in schools with the highest concentration of Hispanic students. Relative to teachers from other racial or ethnic backgrounds, white teachers teach in schools with the fewest poor and lowest-achieving students. Compared to teachers from early-entry pathways, college-recommending teachers teach in schools with the lowest concentrations of black, Hispanic, poor, and lowest-achieving students; TFA teachers, in particular, work in schools with the highest proportion of students across these demographic groups.

By most measures that signal teacher quality, Table 3 demonstrates that high quality teachers generally teach in schools with fewer black, Hispanic, poor and low-performing students. This trend holds for LAST score, undergraduate competitiveness, and experience. Exceptions are that teachers from the most competitive colleges teach at schools with higher proportions of Hispanic students than do teachers from the least competitive colleges. Similarly, teachers from the top quartile in LAST scores teach in schools with more Hispanic students than do teachers from the bottom quartile. One possible explanation for these exceptions is that the Teaching Fellows and TFA programs tend to recruit teachers with strong pre-service qualifications and place their teachers in the hardest-to-staff schools which typically have higher proportions of non-white students.

METHODS

Question 1: Which Teachers Are More Likely to Request a Transfer?

To model teachers' choices to apply for a transfer we use logit models at the teacher-level and include all active teachers in NYC. We model the likelihood of applying for transfer as a function of teacher characteristics and fixed-effects for teachers' current schools. The fixed-effects control for both measured and unmeasured characteristics of schools that might affect a teacher's likelihood of applying for transfer. For example, if teachers with one characteristic tended to be in less desirable schools we might think that teachers with that characteristic are more likely to request transfers, unless we account for school-specific differences in applications. With these controls we estimate the extent to which a teacher with a given characteristic is more or less likely to apply relative to a teacher within the same school but without that characteristic. Equation 1 describes these analyses:

$$P_{tsy}(\text{requests transfer}) = \frac{e^f}{1+e^f} \quad where$$
$$f = \beta_0 + X_{tsy}\beta_1 + \delta_y + \mu_s + \varepsilon_{tsy} \tag{1}$$

In the above equation, the probability that teacher *t*, in school *s*, and in year *y* requests a transfer is a function of teacher characteristics X_{tsy} (gender, race, preparation pathway, quality), a school year indicator variable δ_y, school fixed-effects μ_s, and a random error term ε_{tsy}.

Question 2: What Kinds of Teachers Do Schools Want?

To model school choices for hiring teachers, we use application-level models where the likelihood of a school selecting (hiring) an applicant—from the set of applicants to a school—is as a function of teacher characteristics. Equation 2 describes the conditional logit model:

$$P_{ts_{to}y}(\text{hired}) = \frac{e^g}{1+e^g} \quad where \tag{2}$$
$$g = \alpha_0 + X_{as_{to}y}\alpha_1 + \lambda_y + \varpi_{s_{to}} + \varepsilon_{as_{to}y}$$

In equation 2, the probability that teacher t is hired by school s_{to} in year y, conditional on applying to school s_{to}, is a function of teacher characteristics $X_{as_{to}y}$ (gender, race, preparation pathway, quality), a school year indicator λ_y, school fixed-effects $\varpi_{s_{to}}$, and a random error term $\varepsilon_{as_{to}y}$.

Question 3: What Do We Learn From Applications Data That We Would Not Have Learned From Work-History Files Alone?

Finally, we want to assess the additional information gained by using transfer data instead of the work history files that have been used in prior studies. In order to make this comparison, we estimate the likelihood of transferring based on the work-history files of all active teachers in NYC. Using fixed-effects on current schools, we model the likelihood of transferring as a function of teacher characteristics. Equation 3 describes the model:

$$P(\text{transfer}) = \frac{e^f}{1+e^f} \quad \textit{where} \qquad (3)$$
$$f = \beta_0 + X_{tsy}\beta_1 + \delta_y + \mu_s + \varepsilon_{tsy}$$

In equation 3, the probability that teacher t, in school s, and in year y transfers is a function of teacher characteristics X_{tsy} (gender, race, preparation pathway, quality), a school year indicator variable δ_y, school fixed-effects μ_s, and a random error term ε_{tsy}.

RESULTS

Before addressing our three research questions, we look briefly at the kinds of schools from which and to which teachers tend to apply. Table 4 gives the results of our estimates modeling the log of the number of applicants that schools receive per vacancy and of the estimates modeling the log of the number of requests for transfer away from schools per enrollment as a function of school characteristics.[xiv] Because school-level data on the proportion of lowest-achieving students was available only for grades 4 and 8, including this predictor in our analyses removes most high schools and greatly diminishes our sample. Thus, we run analyses both without (Model 1) and with (Model 2) the proportion of lowest-achieving students.[xv]

The kinds of schools that receive the fewest applicants are in many ways similar to the kinds of schools that teachers want to leave. In keeping with previous studies, these schools have higher concentrations of students that are typically underserved—Hispanic, black, low-income, and low-achieving students. Compared to elementary schools, middle schools receive significantly fewer applicants to them and more requests for transfer away from them. Controlling for other school features, middle schools receive about 40 percent fewer applicants to them and about 40 percent more away from them. Additionally, schools with lower attendance rates, fewer experienced faculty, and higher suspension rates receive more requests for transfer away from them. On the other hand, low-crime schools receive more applicants per vacancy to them. School enrollment is the only predictor in our models whose effect is both significant and in the same direction across dependent variables. Low-enrollment schools get more applicants to them and away from them. One possible explanation, though we cannot test it, is that small schools are appealing to teachers because of their intimacy, resulting in more applications. However, once there, teachers find that while some low-enrollment schools do have great benefits, others lack resources or sources of support that larger schools are able to provide given economies of scale.

Given how requests for transfer vary significantly by school type, subsequent analyses rely upon models with school fixed-effects. Such school fixed-effects models compare teachers only to their colleagues currently teaching in the same school so separate teacher effects from school effects on application behaviors. This allows us to estimate how teacher characteristics predict the likelihood of requesting a transfer in ways that account for the fact that certain kinds of teachers sort into certain kinds of schools.

Question 1: Which Teachers Are More Likely to Request Transfers?

As discussed in the introduction, transfer behavior may not be a good measure of teacher preferences because —although teachers prefer to transfer if they apply—they must be selected by a school in order to actually transfer. Here we test whether requests for transfer vary by teacher quality measures and thus separate teachers' choices to enter the applications-for-transfer pool from schools' choices to hire certain applicants. Table 5 presents the estimates in odds ratios for the likelihood of requesting a transfer as a function of teacher characteristics, including our four primary teacher quality measures, race and ethnicity, preparation route, as well as current school fixed-effects.[xvi]

Of all teachers in NYC, teachers with higher pre-service qualifications are more likely to request transfers. Controlling for other teacher characteristics and fixing the effects of their current schools, teachers with higher LAST scores and those from the most competitive colleges are significantly more likely to request transfers. Teachers with 1 standard deviation higher LAST scores are more likely to apply for transfer by a factor of 1.06 to 1.08, depending on model specification. Having graduated from a competitive college increases a teacher's likelihood of requesting a transfer by 10 to 20 percent. These results provide evidence that the increased likelihood to transfer among teachers with better pre-service qualifications is driven, at least in part, by such teachers being more likely to enter the job market in the first place.

Are teachers with higher practice-based measures of quality also more likely to request transfers? Again the results are consistent with prior literature based on work histories—more experienced and more effective (higher value-added to student achievement) teachers are significantly less likely to apply for transfer. In fact, the likelihood of a first year teacher requesting transfer is 1.5 times greater than it is for other teachers. Increasing a teachers' value-added score by 1 standard deviation reduces the odds of requesting a transfer by 10 percent.[xvii] Somewhat unexpectedly, we found that this value-added effect was strongest among middle school teachers. Appendix Table 1, which shows the results at each school level, demonstrates that an increase of 1 standard deviation on value-added reduces the odds of requesting a transfer among middle school teachers by almost 20 percent.

Table 5 also shows a significant relationship between the likelihood of requesting a transfer and a teacher's preparation pathway. In general, teachers from early-entry (alternative) routes are more likely to request transfers than are teachers from college-recommended (traditional) pathways. Across preparation routes and models, the odds that an early-entry teacher will enter the applications pool are a factor of between 1.1 and 1.5 times higher than for a college-recommending teacher. The exception is TFA teachers who are significantly less likely to request transfers than college-recommending teachers. This is unsurprising given that TFA teachers have a programmatic commitment to serve in certain kinds of schools for 2 years, so are unlikely to enter the applications pool during this time.

Teacher race and ethnicity also predict requests for transfer. Black and Hispanic teachers are significantly less likely to apply for transfer than are white teachers working in the same schools. Being black or Hispanic decreases the odds of applying for transfer about as much as a 4 standard deviation increase in effectiveness. When we ran these models without school fixed-effects, black and Hispanic teachers were significantly more likely to apply for transfer.[xviii] Taken together, these results suggest that black and Hispanic teachers tend to teach in schools from which teachers are more likely to request transfers in general.

Although our modeling strategy is effective for estimating preferences for certain kinds of teachers across schools, perhaps a more policy-relevant concern is whether these preferences may vary across different kinds of teachers and schools. For example, teachers may base their preferences upon the "fit" or "match" they may have with schools. To begin to examine this fit hypothesis, we include interactions between teachers' and students' on race and academic achievement. Appendix Table 4 presents estimates for the effects of these interactions on likelihood of applying. It shows that black teachers are less likely to apply for transfer from schools with higher concentrations of black students; likewise, Hispanic teachers are less likely to apply for transfer from schools with higher concentrations of Hispanic students. Given that these findings indicate that similarity between teachers and student demographics may drive teacher preferences, it seems likely that teachers with higher LAST scores would be more likely to apply away from schools with higher concentrations of lowest-achieving students. However, Appendix Table 4 shows that, although teachers with higher LAST scores are more likely to apply for transfer in general, this effect is not higher in schools with higher proportions of lowest-achieving students. Similarity appears to affect preferences in regards to race, but not with regard to academic achievement.

A major obstacle to identifying the preferences among certain kinds of teachers to apply for transfer is disentangling these teacher preferences from school preferences to push out certain kinds of teachers. Are white or less experienced teachers, for example, more likely to enter the applications pool because these types of teachers prefer to do so? Or, alternatively, are these teachers more likely to enter the applications pool because schools are more likely to push them out of their current placements, leading teachers to seek new jobs? We make some headway in disentangling these explanations by identifying, and removing, teachers who were excessed. We began by identifying schools in our work history file that existed in either 2006–2007 or 2007–2008 but were absent the subsequent year. By identifying teachers who were in these schools during their final year of operation, we were able to remove all teachers who were excessed as a result of school closure. In total, we identified 75 schools that closed over 2 years, and dropped 992 teachers associated with these schools. We then used human resources data from the NYC Department of Education to identify an additional 1,464 teachers who had transferred as a result of being excessed for other factors beyond school closure. After omitting a total of 2,456 excessed teachers, we replicated our models and obtained similar results.[xix]

Dropping excessed teachers in these ways gave us more confidence that our models had estimated the preferences of certain kinds of teachers. However, there are likely other ways that schools push out teachers that may be difficult to observe and that our data cannot capture. It is feasible, for example, that school administrators could make life difficult for some teachers (for example, assigning too many class preparations or classes outside of a teacher's specialty, assigning teachers to the most difficult classrooms[xx]) as a way to encourage these teachers to apply for transfer. Moreover, it is quite possible that schools might systematically push out certain kinds of teachers, for example, those of lower quality.[xxi] Thus, some of the associations we observe may result from more subtle counseling out of certain kinds of teachers by schools, as opposed to preferences among certain kinds of teachers. Even so, we suspect that the number of remaining teachers who are affected in these ways would be relatively small and unlikely to alter our results significantly.

In summary, we find evidence that teachers with stronger pre-service qualifications are more likely to seek transfer. This result is consistent with the hypothesis that such teachers likely have better alternative options and are therefore less likely to stay at a job that is not satisfying. We also find that teachers who are higher on practice-based measures of quality are less likely to seek transfer. A possible explanation for this pattern is that having success with improving student achievement increases teachers' satisfaction with their jobs and placements. That more experienced teachers are less likely to request transfers also makes intuitive sense: Those who have been teaching longer are more likely to have already found a better workplace match. Finally, Teaching Fellows are more likely to request transfers, and Teach for America, black, and Hispanic teachers are less likely.

Question 2: What Kinds of Teachers Do Schools Want?

To model the likelihood of being hired as a function of teacher characteristics, we structure our data at the application-level. By using a conditional logit model we are able to estimate the likelihood of being hired conditional on the set of applicants who had applied to a given school. Table 6 presents the results.[xxii] As mentioned before, it would be more desirable to know which teachers received offers than merely who was hired. Though imperfect, knowing which kinds of teachers schools tend to hire gets us closer to understanding school demand for certain kinds of teachers than most prior research, which used transfer data as a way to estimate school preferences for teachers.

Across our four main teacher quality measures, schools are more likely to hire "higher quality" teachers. Schools are significantly more likely to hire teachers with better pre-service qualifications—LAST score and being from a most competitive college. Schools are also significantly more likely to hire more experienced and more effective teachers.[xxiii] The effect of 1 year of experience is comparable in size to being from a competitive undergraduate college, increasing the likelihood of being hired by 10 percent. Being an effective teacher also increases the likelihood of successfully transferring. An improvement in a teacher's value-added score of 1 standard deviation increases the likelihood of being hired by 20 percent.[xxiv] This result is somewhat surprising given that school hiring authorities do not have access to teachers' value-added measures of effectiveness.

Controlling for other teacher attributes, black and Hispanic teachers are less likely than white teachers to enter the applications pool; however, those who do so have a much higher likelihood of getting hired. Hispanic teachers appear to be in particularly high demand. Schools are about 1.5 times more likely to hire a Hispanic teacher as compared to a white one, other things equal. Black teachers are about 1.3 times more likely than white teachers to be hired. Appendix Table 3 demonstrates that high schools, in particular, prefer to hire Hispanic teachers, where the odds of being hired if Hispanic are over 1.7 times the odds of being hired if white. The hiring advantage that black teachers have over white teachers mostly occurs in middle and high schools, whereas there is no statistically significant difference at the elementary level.

Table 6 also indicates that the likelihood of being hired varies by preparation pathway, even when controlling for other teacher characteristics that may vary by pathway. As compared to college-recommending teachers, schools are significantly more likely to hire Teaching Fellows (an increase in the odds ratio by about 30 percent) and Teach for America (an increase in the odds ratio by a factor of 1.7 to 2.0) teachers. As shown in Appendix Table 3, Teaching Fellows have the strongest advantage of being hired at high schools while TFA teachers are more likely to be hired at middle schools. In fact, the odds of being hired by a middle school are over three times greater for TFA teachers than for college-recommending teachers, even in the most conservative estimates.

Though TFA teachers are the only early-route teachers less likely than college-recommending teachers to enter the applications pool in the first place, they are the teachers with the highest probability of getting hired. Given that we control for LAST scores and college competitiveness, schools' preferences for TFA teachers may reflect other academic qualifications or characteristics on which TFA selects its members, such as leadership skills and responsibility. What does account for this apparent school preference for hiring TFA teachers is a compelling question for further study. Although teachers from "other" pathways are significantly more likely to enter the applications pool than college-recommending teachers, they are significantly less likely to get hired.

As described last section, we found evidence that similarity between teacher and student characteristics affect the decision to apply for transfer. Here we assess whether teacher-student similarity also influences hiring decisions. Appendix Table 4 presents estimates for the likelihood of being hired as a function of interactions between teacher and student characteristics. Across characteristics, we find that schools are more likely to hire teachers who share the characteristics of the student body. Schools with more black students are more likely to hire black teachers; schools with more Hispanic students are more likely to hire Hispanic teachers; and schools with more low-achieving students are more likely to hire teachers with lower LAST scores. These results, potentially resulting from differential school preferences, might also be driven by differences across schools in their ability to hire their applicants. We do not observe job offers, only the final match. Some schools are likely to have more difficulty securing their first choice applicant, as that applicant may have other preferable job offers.

Question 3: What Do We Learn From Applications Data That We Would Not Have From Work History Files Alone?

To unpack the methodological advantages of having access to applications data, let us first consider what we would have known without it. Table 7 presents results using work-history files only—examining who moves and stays among all active NYC teachers over the same 2 academic years.[xxv] We see that teachers with higher pre-service qualifications—better LAST scores and degrees from competitive colleges—are more likely to transfer. On the other hand, more experienced and more effective teachers are less likely to transfer, though the effect of teacher effectiveness is non-significant.[xxvi]

We also find that the likelihood of transfer is not significantly different for black and Hispanic teachers than it is for white ones. However, the direction of our coefficients are in keeping with prior research that has found significant differences between these groups—namely, white teachers are more likely to transfer than black or Hispanic teachers from the same school. Finally, consistent with our review of the literature, our results indicate that teachers from early-entry pathways into teaching are significantly more likely to transfer than are college-recommending teachers. This is true for all but TFA teachers who are significantly less likely to transfer, again probably reflecting TFA's policy of placing teachers in difficult-to-staff schools and requiring 2 years of service. The likelihood of transferring is particularly high for Teaching Fellows. Being from this preparation pathway increases the odds of transferring by almost as much as being a first year teacher.

These results provide information about which teachers are more likely to transfer. What we don't know from the work-history files is the extent to which teacher or school preferences drive these results. We might inappropriately speculate from the results in Table 7 that schools prefer hiring ineffective or inexperienced teachers. Our analyses of applications data reveal, however, that schools are much more likely to hire teachers who demonstrate higher quality on these practice-based measures. In fact, by differentiating school and teacher preferences using applications data, we find a demand among schools for teachers exhibiting quality on both practice-based measures and pre-service qualifications. The fact that pre-service qualifications predict transferring and practice-based quality predict staying is explained by teacher preferences (supply) to enter the jobs market rather than school preferences (demand) for certain teachers. Regardless of how quality is signaled, higher quality teachers are more likely to get hired than lower quality ones; teachers who appear higher on pre-service qualifications and lower on practice-based quality are more likely to transfer because these groups are significantly more likely to request transfers in the first place.

Looking beyond these two sets of teacher quality measures, our analyses of applications data shed light on the relationships between other teacher characteristics that could proxy for quality and likelihood of transfer. In particular, our analysis of work-history files reveals no significant differences in likelihood of transfer across teacher race. The work history data might be interpreted falsely to show that there are no differences in hiring by teacher race when, in fact, strong differences on both the supply and demand sides become evident when analyzing applications data. We find that black and Hispanic teachers are significantly less likely than white teachers to request transfer. At the same time, among teachers who enter the applications pool, black and Hispanic teachers are significantly more likely than white teachers to get hired. Because the weak supply of black and Hispanic teachers is cancelled out by the greater demand for them, work history files do not reveal significant differences in transferring by race. These differences were evident only upon inspecting applications data.

Finally, our analysis of work-history files indicates that teachers from Teaching Fellows are more likely to transfer than teachers from college-recommending programs, while TFA teachers are actually less likely to transfer. Without the applications data, however, we cannot be sure whether teachers from early-entry pathways (TFA and Teaching Fellows) are more likely to transfer because they are more likely to choose to enter the applications pool or because schools prefer to hire them. We find that a combination of supply- and demand-side explanations account for this variation by preparation route. Given that there is significantly higher supply and demand for Teaching Fellows, it is no surprise that Teaching Fellows have the highest likelihood of transferring (the odds are 1.3 to 1.4 times greater than college-recommending teachers). Demand-side explanations seem to account for the relatively higher likelihood of transfer among TFA teachers. Our analysis of applications-for-transfer data reveal that, among all preparation routes, TFA teachers are in highest demand (according to our estimates of who gets hired)—a finding that was hidden when examining work history files alone. Despite being in high demand, TFA teachers are the least likely to transfer because they are the least likely to enter the applications pool in the first place.

DISCUSSION

This study contributes to a recent and growing body of research examining the relationship between teacher quality and career pathways. Consistent with prior work, we find that this relationship depends upon the dimension of quality under study. In particular, pre-service qualifications (LAST teacher certification exam scores and being from a competitive college) predict greater teacher migration while practice-based quality measures (teaching experience and value-added to student achievement) predict lower teacher migration. Our research adds to prior work in pulling apart the role of teacher preferences from the role of school preferences in explaining the driving mechanisms behind this observed difference in transfer patterns by type of quality. We find that schools are significantly more likely to hire teachers across all four dimensions of teacher quality. Thus, differences in transfer patterns exist not because of school preferences but because teachers with pre-service qualifications are more likely to enter the jobs market, while more experienced and more effective teachers are less likely to do so.

In addition to examining quality as defined above, this study addresses two additional measures that may proxy for quality—teachers' race or ethnicity and their preparation pathway into the profession. Although these two characteristics are not direct measures of quality, they may represent qualities that schools look for in hiring decisions. The over-representation of white teachers relative to student demographics suggests that non-white teachers may be in demand. Similarly, the differences in preparation or recruitment methods across pathways may lead schools to seek out teachers from particular pathways. Prior studies that control for school, district, and other teacher characteristics find that black and Hispanic teachers are more likely to stay in schools from year-to-year than are white teachers.[xxvii] Among transferring teachers, one possible explanation is that black and Hispanic teachers are less likely to apply for transfer;

another explanation might be that they are requesting transfers at similar rates, but school hiring practices give white teachers preference. Our analysis of applications data provides support for the former, supply-side explanation and evidence against the latter, demand-side explanation. Black and Hispanic teachers are significantly less likely than white teachers to enter the applications pool to begin with; however, when black and Hispanic teachers enter the applications pool they are far more likely to get hired.

While prior work typically finds that teachers from early-entry pathways leave teaching at higher rates than do teachers from college-recommending programs, we know less about whether teachers from early-entry pathways are more likely to apply for transfer or, when they do apply, whether they are more likely to get hired. Applications data reveal that Teaching Fellows are more likely to apply for transfer than are college-recommending teachers, while TFA teachers—who have committed to stay in schools for two years—are not. On the other hand, schools are more likely to hire early-entry teachers than those from a college-recommending pathway, especially TFA corps members. Given that our models include school fixed-effects, differential applying by preparation pathway away from and to different kinds of schools cannot explain observed pathway effects. Because these models also control for other teacher characteristics—including various measures of teacher quality, race, age, and gender—differential sorting of different kinds of teachers into various pathways based on these measured characteristics cannot account for these pathway effects either.

Our study also makes methodological contributions. Most notably, we are aware of no other study that has used applications data to examine the relationship between teacher characteristics and transfer. We have made the case that using applications data has many advantages over using work history files alone. Perhaps what is most significant is applications data allows us to get closer to estimating both teacher and school preferences and move away from speculation on what is driving patterns in teacher migration.

Our analyses of applications data also has implications for how to improve on this work. In particular, gaining access to information on which teachers received job offers, in addition to hiring information, would improve future efforts to model school preferences for teachers. Moreover, knowing which schools teachers choose out of those that make job offers to them would help estimate teacher preferences for certain kinds of schools. In trying to model the preferences of certain kinds of teachers to apply for transfer, one of our biggest obstacles has been separating out teachers' preferences to leave from schools' tendencies to push out certain kinds of teachers. We have made significant headway by identifying and dropping teachers that have been excessed; however, there are certainly other, more subtle and difficult-to-observe, ways that schools may push out teachers. Identifying these, collecting data on them, and controlling for them would make us more certain that we are indeed estimating preferences among certain kinds of teachers rather than differential pushing out of certain kinds of teachers by schools. Another way to build on this work would be to study other measures of teacher quality beyond those included here. For example, researchers are currently developing standards-based instruments of teacher practice that may better measure teacher quality or, at least, may provide measures of aspects of teacher quality not captured by the variables included in this study (Grossman et al., 2010). Future studies might examine whether scores on these instruments are similarly associated with transferring and hiring patterns. Finally, our preliminary analyses suggest that similarity between teacher and student body may help to explain applications and hiring processes. We intend to examine this process in greater detail in a separate study.

Disentangling supply from demand in teacher transfers has the potential to inform policy. Knowing what kinds of teachers try to leave schools and what kinds of teachers schools want to hire can help target policy to attract and retain better quality teachers. As described above, our access to applications data accompanied a substantial change in transfer policy in New York from seniority-based transfers to an open-market process. Our results demonstrate that, under this new system, schools are selecting higher quality teachers—imperfectly measured, but measured on multiple dimensions—from the pool of teachers available to them. The results also show that teachers who are more effective, holding all else equal, are less likely to seek transfer. These results may suggest some positive dynamics in an open-market system. For example, schools appear to be choosing, on average, in the best interest of their students rather than according to alternative goals that might lead them to choose less effective teachers. However, this study is not an evaluation of seniority-based or market-based transfer policies. While hiring on quality under a market-based system may benefit the individual school, it may well have unintended negative consequences for the system as a whole. In particular, low-performing or otherwise difficult-to-staff schools may lose effective teachers who find it easier to transfer to more appealing schools in a market-based system. In other work, we are examining whether the policy changes in NYC have resulted in differential sorting of high quality teachers away from lower-performing schools and the effects that teacher migration patterns may have on student achievement at different kinds of schools. The current paper is not a direct evaluation, but instead it is a source of information on the factors driving teachers' and schools' decisions. Understanding these preferences can aid in the design of policies aimed to retain the best teachers in schools where they are needed the most.

TABLES

Table 1. Descriptive Statistics on Active Teachers in NYC

	Overall	Appliers	Movers
Number of active teachers	80,898	11,076	4,693
Teacher Demographic Information			
Proportion female	0.75	0.71	0.70
Proportion white	0.62	0.59	0.56
Proportion black	0.19	0.21	0.23
Proportion Hispanic	0.13	0.12	0.14
Proportion “other,” non-white	0.06	0.08	0.08
Age (mean)	41.33	38.55	37.45
Teacher Preparation Route			
Proportion college-recommending	0.43	0.36	0.32
Proportion TF	0.12	0.18	0.23
Proportion TFA	0.02	0.01	0.02
Proportion temporary license	0.22	0.22	0.22
Proportion “other” path	0.21	0.23	0.21
Teacher Pre-Service and Practice-Based Quality Measures			
Proportion most competitive college	0.33	0.38	0.41
LAST (mean)	247.83	249.81	252.84
Experience (mean)	7.49	5.26	5.08
Math value-added (mean)	-0.35	-0.36	-0.34

Table 2. School Characteristics (School-Level Averages over 2003-2006)

Variable	Observations	Mean	SD
Proportion elementary	1366	0.54	0.50
Proportion middle school	1366	0.20	0.39
Proportion high school	1366	0.26	0.44
% Female	1360	49.82	7.43
% Black	1360	36.29	28.77
% Hispanic	1360	40.15	25.58
% Asian	1360	10.86	15.57
% ELL	1297	13.23	13.72
% Free lunch	1304	69.68	22.84
Attendance rate	1304	90.31	5.81
Proportion new (1998)	1366	0.34	0.47
% Faculty 5+ years experience	1351	47.54	18.73
Enrollment/100	1360	7.46	6.16
% Special ed.	1294	4.56	4.30
Suspensions/enrollment	1349	0.05	0.09
Proportion high crime	1225	0.27	0.44
% Level 1 (lowest) math achievement	900	14.51	12.79

Table 3. Characteristics of Current School Placements by Teacher Characteristics

Teacher characteristics		School characteristics			
		% Black students	% Hispanic students	% Free lunch	% Lowest-level math
Teacher race/ethnicity	White teachers	27.48	38.44	63.96	13.31
	Black teachers	55.81	33.92	75.89	19.49
	Hispanic teachers	26.94	57.10	77.51	16.86
	Other teachers	31.19	38.90	68.63	15.19
Teacher preparation pathway	College-rec.	30.41	37.55	66.64	12.73
	Teaching fellows	37.36	48.34	75.28	19.07
	TFA	37.77	57.06	84.03	23.32
	Temp. license	36.56	42.19	70.60	18.35
	Other	35.09	38.77	67.47	15.63
Barron's college rating	Least competitive	34.42	38.58	69.31	15.28
	Less competitive	34.66	39.48	70.12	14.79
	Competitive	28.77	40.43	65.25	14.21
	Most competitive	31.62	42.97	66.61	14.86
LAST score	Quartile 1 (low)	37.89	41.77	74.26	16.62
	Quartile 2	34.79	39.83	70.46	15.09
	Quartile 3	32.64	40.78	68.06	15.18
	Quartile 4 (high)	32.60	43.55	67.53	16.31
Teaching experience	Quartile 1 (low)	34.55	42.86	70.63	16.12
	Quartile 2	33.97	40.19	69.26	15.48
	Quartile 3	32.94	38.89	67.77	14.39
	Quartile 4 (high)	31.57	37.63	65.59	14.40
Math value-added to student achievement	Quartile 1 (low)	27.93	39.94	71.20	17.21
	Quartile 2	32.14	39.67	71.57	16.34
	Quartile 3	35.75	39.46	73.33	15.22
	Quartile 4 (high)	38.22	40.45	75.78	13.60

Table 4. Modeling Requests for Transfer to and Away from Schools as a Function of School Characteristics (School-Level)

Variables	**Log (Applicants Away/Enrollment)**		**Log (Applicants to/Vacancies)**	
	Model 1	Model 2	Model 1	Model 2
Middle school	0.3847***	0.5398~	-0.4258***	0.4183
	(0.0668)	(0.3072)	(0.0777)	(0.3899)
High school	0.0303	0.3029	0.0254	0.6662
	(0.0898)	(0.3452)	(0.0997)	(0.4230)
Other non-elementary	0.5491	0.7780*	-0.8834*	-0.5647
	(0.3605)	(0.3886)	(0.3885)	(0.4364)
% Black students	0.0072***	0.0020	-0.0059**	-0.0047*
	(0.0017)	(0.0020)	(0.0019)	(0.0022)
% Hispanic students	0.0059**	0.0008	-0.0039~	-0.0039
	(0.0020)	(0.0023)	(0.0022)	(0.0025)
% Asian students	0.0027	0.0018	0.0041	0.0044
	(0.0024)	(0.0027)	(0.0025)	(0.0029)
% ELL students	-0.0040~	-0.0010	-0.0008	0.0028
	(0.0021)	(0.0041)	(0.0026)	(0.0047)
% Free lunch	0.0082***	0.0100***	-0.0041*	-0.0062*
	(0.0017)	(0.0022)	(0.0019)	(0.0025)
Attendance rate	-0.0193**	-0.0682***	0.0042	-0.0369
	(0.0063)	(0.0189)	(0.0075)	(0.0227)
New school (1998)	0.1289	0.1232	0.0021	-0.0399
	(0.1144)	(0.1711)	(0.1306)	(0.2034)
% Teachers 5+ experience	-0.0132***	-0.0164***	0.0002	0.0057*
	(0.0017)	(0.0024)	(0.0019)	(0.0028)
Enrollment/100	-0.0271***	-0.0492***	-0.0161**	-0.0079
	(0.0044)	(0.0093)	(0.0049)	(0.0110)
New school * enrollment	-0.0081	-0.0161	0.0092	0.0256
	(0.0178)	(0.0239)	(0.0201)	(0.0279)
% Special ed. students	0.0105~	0.0048	-0.0054	-0.0074
	(0.0056)	(0.0080)	(0.0072)	(0.0096)
Suspensions/enrollment	0.9158***	1.3717**	0.3633	0.1143
	(0.2590)	(0.5258)	(0.3102)	(0.8852)
School crime (highest 25%)	0.0896	-0.0526	-0.2500**	-0.3181**
	(0.0691)	(0.0855)	(0.0780)	(0.1007)
% Level 1 in math		0.0090*		-0.0063
		(0.0037)		(0.0044)
8th Grade exam indicator		-0.2999		-0.7166~
		(0.3065)		(0.3885)
Constant	-3.5646***	1.4412	3.9871***	7.5599***
	(0.6490)	(1.8123)	(0.7553)	(2.1658)
Observations	1108	802	1012	731
Adj. r-squared	0.4381	0.4207	0.1971	0.2466
R-Squared	0.4462	0.4337	0.1842	0.2276

Table 5. Modeling Who Applies for Transfer as a Function of Teacher Characteristics (Fixed-Effects on Current School, Estimates as Odds Ratios)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Female	0.9714	0.9844	0.9815	0.9822	0.9643
	(0.0261)	(0.0307)	(0.0306)	(0.0306)	(0.0755)
Black teacher	0.7201***	0.7525***	0.7270***	0.7277***	0.7107***
	(0.0246)	(0.0297)	(0.0286)	(0.0287)	(0.0648)
Hispanic teacher	0.8149***	0.8401***	0.8032***	0.8034***	0.6516***
	(0.0309)	(0.0355)	(0.0339)	(0.0339)	(0.0683)
Other, non-white teacher	1.2024***	1.0838	1.0753	1.0765	0.8163
	(0.0512)	(0.0624)	(0.0619)	(0.0619)	(0.1201)
Indicator year 2	0.8323***	0.8563***	0.8505***	0.8499***	0.8418**
	(0.0189)	(0.0223)	(0.0222)	(0.0222)	(0.0502)
Experience (years)	0.9314***	0.9338***			0.9221***
	(0.0042)	(0.0047)			(0.0123)
Teaching fellow	1.2018***	1.2409***	1.3646***	1.3602***	1.4626***
	(0.0422)	(0.0505)	(0.0551)	(0.0549)	(0.1480)
TFA	0.2722***	0.4396***	0.4672***	0.4680***	0.5213*
	(0.0276)	(0.0575)	(0.0612)	(0.0613)	(0.1516)
Temporary license	1.0838*	1.0909*	0.9951	1.0005	1.1801~
	(0.0380)	(0.0415)	(0.0366)	(0.0369)	(0.1051)
Other path	1.1287***	1.1107**	1.1356**	1.1340**	1.1438
	(0.0375)	(0.0435)	(0.0443)	(0.0443)	(0.1158)
LAST	1.0020***	1.0025***	1.0026***	1.0026***	1.0012
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0012)
Age	0.9979	0.9946***	0.9883***	0.9869***	0.9922*
	(0.0013)	(0.0015)	(0.0014)	(0.0015)	(0.0038)
Most competitive college		1.1027**	1.1038**	1.1046***	1.2067*
		(0.0331)	(0.0332)	(0.0332)	(0.0897)
First year indicator			1.4551***	0.9938	
			(0.0574)	(0.1360)	
First year * age				1.0124**	
				(0.0043)	
Teacher value-added (standardized)					0.9044**
					(0.0343)
Observations	88917	70440	70440	70440	10660
Chi^2	1174.8908	883.9484	776.4900	784.8708	212.0278
Number of schools	1399	1352	1352	1352	618
P-value	0	0	0	0	0

**** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.1$; standard errors in parentheses; results as odds ratios*

Table 6. Modeling the Likelihood of Being Hired as a Function of Teacher Characteristics (Application-Level, Fixed-Effects on Schools to which Teachers Apply, Estimates as Odds Ratios)

Variables	**Model 1**	**Model 2**	**Model 3**
Female	1.0596	1.0797	0.9722
	(0.0458)	(0.0543)	(0.1078)
Black teacher	1.3415***	1.3315***	1.2319~
	(0.0707)	(0.0811)	(0.1482)
Hispanic teacher	1.5125***	1.5253***	1.6136**
	(0.0890)	(0.1006)	(0.2423)
Other, non-white teacher	0.7889***	0.9563	0.7836
	(0.0565)	(0.0863)	(0.1403)
Year 2007 indicator	1.4633***	1.4406***	1.3023**
	(0.0607)	(0.0686)	(0.1283)
Experience	1.0850***	1.0792***	1.1155***
	(0.0074)	(0.0082)	(0.0211)
Teaching fellow	1.2713***	1.2798***	1.1240
	(0.0671)	(0.0775)	(0.1484)
TFA	2.0387***	1.6650**	2.6506**
	(0.2807)	(0.2852)	(0.9744)
Temporary license	1.1080~	1.1307~	0.9211
	(0.0674)	(0.0737)	(0.1305)
Other pathway	0.8658*	0.8201**	0.9463
	(0.0498)	(0.0560)	(0.1368)
LAST	1.0064***	1.0051***	1.0069***
	(0.0008)	(0.0009)	(0.0018)
Age	0.9646***	0.9667***	0.9677***
	(0.0023)	(0.0028)	(0.0056)
Most competitive college		1.1060*	
		(0.0529)	
Teacher value-added (standardized)			1.2045***
			(0.0567)
Observations	103442	72341	9310
P-value	0	0	0
Number of schools	1024	946	410
Chi^2	779.7193	463.1385	143.6215
**** p < 0.001, ** p < 0.01, * p < 0.05, ~ p < 0.1; standard errors below estimates; estimates as odds-ratios*			

Table 7. Modeling the Likelihood of Transfer as a Function of Teacher Characteristics (Fixed-Effects on Current School, Estimates as Odds Ratios)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Female	0.9874	1.0235	1.0210	1.0220	0.8415*
	(0.0327)	(0.0397)	(0.0396)	(0.0396)	(0.0721)
Black teacher	1.0444	1.0491	1.0300	1.0319	1.1076
	(0.0427)	(0.0501)	(0.0491)	(0.0492)	(0.1118)
Hispanic teacher	1.0056	1.0055	0.9785	0.9780	0.9248
	(0.0469)	(0.0531)	(0.0516)	(0.0515)	(0.1096)
Other, non-white teacher	1.2123***	1.2454**	1.2348**	1.2376**	1.2920~
	(0.0655)	(0.0889)	(0.0882)	(0.0883)	(0.1822)
Year 2007 indicator	1.1107***	1.1023**	1.1130**	1.1116**	1.1112
	(0.0314)	(0.0358)	(0.0364)	(0.0363)	(0.0751)
Experience	0.9534***	0.9589***			0.9469***
	(0.0052)	(0.0059)			(0.0141)
Teaching fellow	1.3209***	1.3068***	1.3893***	1.3837***	1.3462**
	(0.0578)	(0.0672)	(0.0709)	(0.0706)	(0.1548)
Teach for America	0.4745***	0.6289**	0.6597**	0.6608**	0.5769*
	(0.0517)	(0.0948)	(0.0994)	(0.0997)	(0.1480)
Temporary license	1.1667***	1.1730***	1.1277**	1.1379**	1.2745*
	(0.0508)	(0.0553)	(0.0518)	(0.0524)	(0.1348)
Other preparation route	1.1373**	1.1119*	1.1198*	1.1163*	1.1644
	(0.0481)	(0.0560)	(0.0563)	(0.0562)	(0.1303)
LAST	1.0028***	1.0022**	1.0022**	1.0022**	1.0018
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0014)
Age	0.9903***	0.9882***	0.9847***	0.9825***	0.9839***
	(0.0017)	(0.0019)	(0.0018)	(0.0019)	(0.0044)
Most competitive college		1.1293**	1.1304**	1.1310**	
		(0.0426)	(0.0426)	(0.0427)	
First year teacher			1.4498***	0.7881	
			(0.0730)	(0.1349)	
First year * age				1.0199***	
				(0.0053)	
Teacher value-added (standardized)					0.9472
					(0.0395)
Observations	83265	64078	64078	64078	10676
Chi^2	443.4306	315.6424	320.0849	333.7515	82.6130
Number of schools	1309	1231	1231	1231	538
P-value	0	0	0	0	0
**** p < 0.001, ** p < 0.01, * p < 0.05, ~ p < 0.1; standard errors in parentheses; estimates as odds ratios*					

APPENDICES

Appendix Table 1. Modeling Who Applies for Transfer as a Function of Teacher Characteristics, by School Level (Fixed-Effects on Current School, Estimates as Odds Ratios)

	Elementary		**Middle**		**High**
Teacher characteristics	Model 1	Model 2	Model 3	Model 4	Model 5
Female	0.9193	0.9057	1.0666	1.0615	0.9826
	(0.0526)	(0.0977)	(0.0620)	(0.1273)	(0.0531)
Black teacher	0.6917***	0.7135**	0.7377***	0.6817*	0.8393*
	(0.0428)	(0.0832)	(0.0581)	(0.1070)	(0.0678)
Hispanic teacher	0.8318**	0.7107**	0.7755**	0.5329**	0.9825
	(0.0510)	(0.0899)	(0.0691)	(0.1058)	(0.0870)
Other, non-white teacher	1.1856~	0.9470	0.9371	0.6062*	1.1186
	(0.1031)	(0.1809)	(0.1159)	(0.1484)	(0.1220)
Indicator year 2	0.7813***	0.7895**	0.8431**	0.8871	0.9205
	(0.0304)	(0.0586)	(0.0452)	(0.0950)	(0.0487)
Years experience	0.9328***	0.9295***	0.9348***	0.9177***	0.9391***
	(0.0071)	(0.0153)	(0.0100)	(0.0223)	(0.0097)
Teaching fellow	1.3939***	1.5511***	1.2032*	1.3793~	1.1614~
	(0.0871)	(0.1985)	(0.0994)	(0.2393)	(0.0946)
TFA	0.3628***	0.4829~	0.4698***	0.4931~	0.6003
	(0.0743)	(0.2071)	(0.0928)	(0.2085)	(0.2354)
Temporary license	1.1017	1.2625*	0.9791	0.9272	1.1730*
	(0.0651)	(0.1391)	(0.0754)	(0.1523)	(0.0912)
Other path	1.1303*	1.1125	1.0902	1.1219	1.0536
	(0.0652)	(0.1396)	(0.0905)	(0.2067)	(0.0870)
LAST	1.1046***	1.0468	1.0574~	1.0019	1.0643~
	(0.0269)	(0.0493)	(0.0350)	(0.0649)	(0.0366)
Age	0.9838***	0.9846**	1.0004	1.0015	1.0060*
	(0.0025)	(0.0050)	(0.0031)	(0.0063)	(0.0029)
Most competitive college	1.0872~	1.1946~	1.1428*	1.2382~	1.0444
	(0.0509)	(0.1118)	(0.0689)	(0.1605)	(0.0611)
Teacher value-added (standardized)		0.9412		0.8070**	
		(0.0422)		(0.0622)	
Observations	35135	7330	13179	3061	16427
Chi^2	659.1815	147.2906	208.8652	86.3841	90.9227

Appendix Table 2. Modeling Who Applies for Transfer as a Function of Teacher Characteristics (Fixed-Effects on Current School, Excessed Teachers & Closing Schools Dropped, Estimates as odds Ratios)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Female	0.9632	0.9804	0.9790	0.9798	0.9545
	(0.0265)	(0.0312)	(0.0312)	(0.0312)	(0.0763)
Black teacher	0.7253***	0.7566***	0.7323***	0.7332***	0.7243***
	(0.0254)	(0.0305)	(0.0295)	(0.0295)	(0.0672)
Hispanic teacher	0.8146***	0.8338***	0.7958***	0.7961***	0.6501***
	(0.0315)	(0.0359)	(0.0343)	(0.0343)	(0.0697)
Other, non-white teacher	1.1847***	1.0682	1.0606	1.0615	0.7978
	(0.0515)	(0.0627)	(0.0622)	(0.0623)	(0.1197)
Indicator year 2	0.8145***	0.8391***	0.8331***	0.8324***	0.8399**
	(0.0189)	(0.0222)	(0.0222)	(0.0222)	(0.0509)
Years experience	0.9300***	0.9324***			0.9183***
	(0.0043)	(0.0048)			(0.0125)
Teaching Fellow	1.1901***	1.2292***	1.3543***	1.3492***	1.3905**
	(0.0423)	(0.0507)	(0.0554)	(0.0552)	(0.1429)
TFA	0.2799***	0.4654***	0.4962***	0.4972***	0.5073*
	(0.0283)	(0.0608)	(0.0648)	(0.0649)	(0.1486)
Temporary license	1.0841*	1.0863*	0.9876	0.9938	1.1779~
	(0.0390)	(0.0423)	(0.0373)	(0.0376)	(0.1066)
Other path	1.1079**	1.0928*	1.1205**	1.1187**	1.0973
	(0.0377)	(0.0437)	(0.0446)	(0.0446)	(0.1134)
LAST	1.0023***	1.0026***	1.0027***	1.0027***	1.0017
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0013)
Age	0.9977~	0.9945***	0.9880***	0.9864***	0.9918*
	(0.0013)	(0.0016)	(0.0015)	(0.0016)	(0.0039)
Most competitive college		1.0981**	1.0985**	1.0994**	1.1985*
		(0.0335)	(0.0335)	(0.0336)	(0.0904)
First year teacher			1.4461***	0.9553	
			(0.0575)	(0.1318)	
First year * age				1.0135**	
				(0.0043)	
Teacher value-added					0.6232**
					(0.1014)
Observations	86551	68711	68711	68711	10361
Chi^2	1153.6519	876.5948	767.3573	777.1013	209.4378
P-value	0	0	0	0	0
Number of schools	1371	1328	1328	1328	599
**** p < 0.001, ** p < 0.01, * p < 0.05, ~ p < 0.1; standard errors in parentheses; results as odds ratios*					

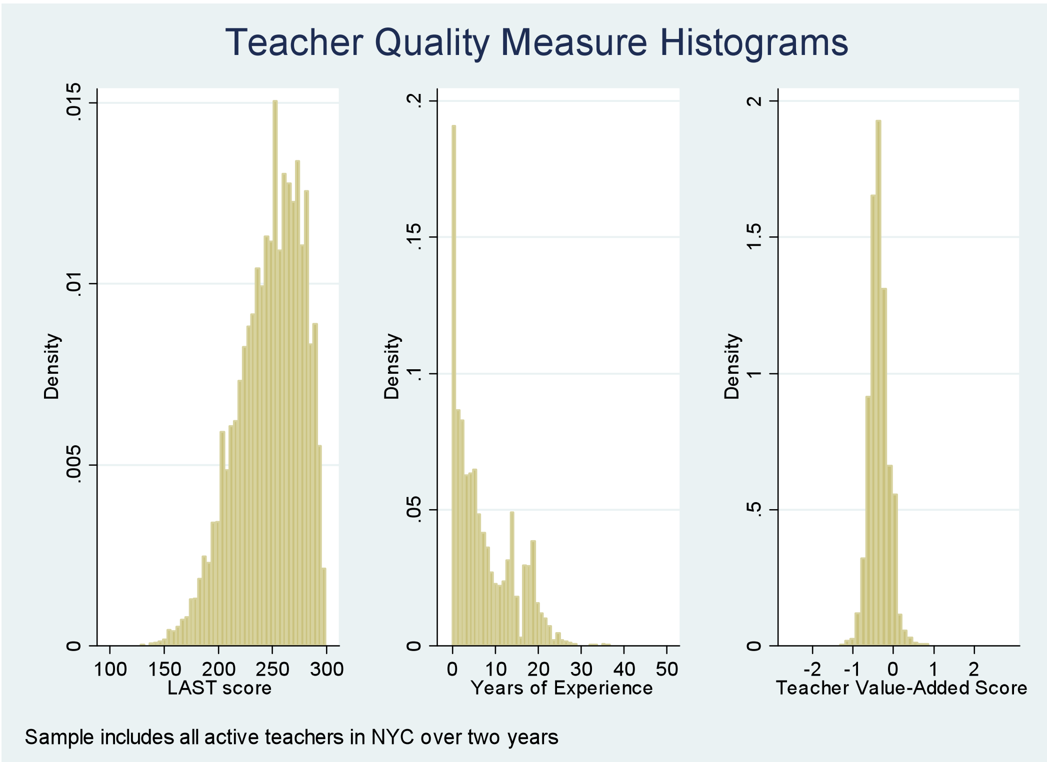
Appendix Table 3. Modeling the Likelihood of Being Hired as a Function of Teacher Characteristics, by School Level (Application-Level, School Fixed-Effects, Estimates as Odds Ratios)

	Elementary		Middle		High
Teacher characteristics	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Female	1.0427	0.8314	1.2644~	1.0030	0.9506
	(0.1021)	(0.1324)	(0.1560)	(0.2388)	(0.0774)
Black teacher	1.0570	0.9313	1.6905***	2.2144**	1.3407*
	(0.1126)	(0.1617)	(0.2348)	(0.5626)	(0.1552)
Hispanic teacher	1.3178**	1.3511	1.3358~	2.4931**	1.8870***
	(0.1410)	(0.2776)	(0.2313)	(0.8770)	(0.2280)
Other, non-white teacher	0.9004	0.8351	0.7810	0.9595	1.2793
	(0.1320)	(0.2332)	(0.1874)	(0.3702)	(0.1949)
Indicator year 2	1.5357***	1.6928***	1.5459***	0.8882	1.3651***
	(0.1190)	(0.2295)	(0.1836)	(0.1977)	(0.1151)
Years experience	1.0680***	1.1281***	1.0564**	1.1596***	1.1151***
	(0.0130)	(0.0276)	(0.0219)	(0.0503)	(0.0156)
Teaching fellow	1.0895	0.9091	1.1103	1.7615~	1.5551***
	(0.1105)	(0.1646)	(0.1759)	(0.5715)	(0.1716)
TFA	1.6543	1.3979	3.1028***	9.9770**	0.8647
	(0.5198)	(0.8212)	(0.9383)	(7.1732)	(0.3474)
Temporary license	1.0696	0.7711	1.6732**	1.4108	0.9821
	(0.1170)	(0.1478)	(0.2662)	(0.4496)	(0.1210)
Other path	0.8015*	0.9932	0.9871	1.5461	0.8183
	(0.0872)	(0.1862)	(0.1733)	(0.5573)	(0.1048)
LAST	1.0026~	1.0071**	1.0037~	1.0056	1.0094***
	(0.0015)	(0.0025)	(0.0022)	(0.0038)	(0.0018)
Age	0.9757***	0.9735***	0.9580***	0.9535***	0.9641***
	(0.0048)	(0.0079)	(0.0069)	(0.0129)	(0.0048)
Most competitive college	1.1460~		1.1077		1.0363
	(0.0938)		(0.1292)		(0.0882)
Teacher value-added (standardized)		1.2313***		1.0309	
		(0.0756)		(0.1103)	
Observations	31714	5648	9398	1506	23555
Chi^2	109.5102	65.2445	132.7638	70.2471	208.1277

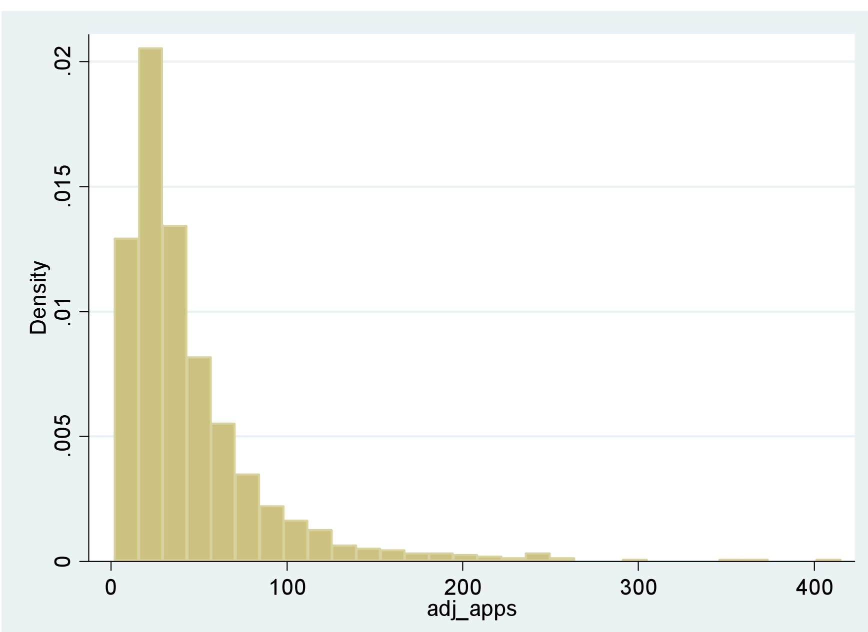
Appendix Table 4. Likelihood of Applying for Transfer and of Being Hired as a Function of Interactions between Teacher and Student Characteristics (School Fixed-Effects, Estimates as Odds Ratios)

	Likelihood of applying			**Likelihood of being hired**		
Teacher characteristics:	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Female	0.9824	0.9792	0.9608	1.0677	1.0704	1.1788*
	(0.0319)	(0.0317)	(0.0400)	(0.0585)	(0.0586)	(0.0980)
Black teacher	1.3401***	0.7442***	0.6921***	0.4936***	1.3327***	1.1410
	(0.1041)	(0.0307)	(0.0346)	(0.0626)	(0.0881)	(0.1035)
Hispanic teacher	0.8544***	1.2667*	0.8021***	1.4480***	0.8257	1.1910~
	(0.0373)	(0.1174)	(0.0419)	(0.1036)	(0.1296)	(0.1183)
Other, non-white teacher	1.0776	1.0927	1.0705	0.9883	0.9849	0.8295
	(0.0641)	(0.0648)	(0.0790)	(0.0943)	(0.0940)	(0.1106)
Indicator year 2	0.8202***	0.8201***	0.7898***	1.4859***	1.4845***	1.7076***
	(0.0221)	(0.0221)	(0.0256)	(0.0749)	(0.0748)	(0.1183)
Years experience	0.9328***	0.9326***	0.9319***	1.0835***	1.0839***	1.0700***
	(0.0050)	(0.0050)	(0.0059)	(0.0089)	(0.0089)	(0.0120)
Teaching fellow	1.2303***	1.2345***	1.2942***	1.2514***	1.2518***	1.2162*
	(0.0518)	(0.0519)	(0.0666)	(0.0822)	(0.0820)	(0.1095)
TFA	0.4493***	0.4357***	0.4558***	1.7162**	1.7078**	2.1907**
	(0.0589)	(0.0572)	(0.0682)	(0.3102)	(0.3088)	(0.5349)
Temporary license	1.1002*	1.1016*	1.0678	1.1021	1.1017	1.2253*
	(0.0437)	(0.0437)	(0.0508)	(0.0775)	(0.0776)	(0.1167)
Other path	1.0990*	1.0994*	1.1443**	0.8458*	0.8464*	0.9243
	(0.0448)	(0.0447)	(0.0552)	(0.0618)	(0.0618)	(0.0889)
LAST	1.0821***	1.0800***	1.1370***	1.0047***	1.0048***	1.0064**
	(0.0183)	(0.0182)	(0.0356)	(0.0010)	(0.0010)	(0.0020)
Age	0.9949**	0.9950**	0.9898***	0.9664***	0.9665***	0.9713***
	(0.0016)	(0.0016)	(0.0020)	(0.0030)	(0.0030)	(0.0041)
Most competitive college	1.0934**	1.0929**	1.0924*	1.1115*	1.1035~	1.1991*
	(0.0340)	(0.0340)	(0.0414)	(0.0576)	(0.0570)	(0.0853)
Black teacher * % black	0.9886***			1.0231***		
	(0.0013)			(0.0024)		
Hispanic teacher * %		0.9923***			1.0120***	
		(0.0016)			(0.0028)	
LAST * % lowest-			0.9978~			0.9996***
			(0.0012)			(0.0001)
Observations	65464	65464	46490	66510	66510	36999
Chi^2	933	881	786	502	417	208
Number of schools	1210	1210	805	836	836	519

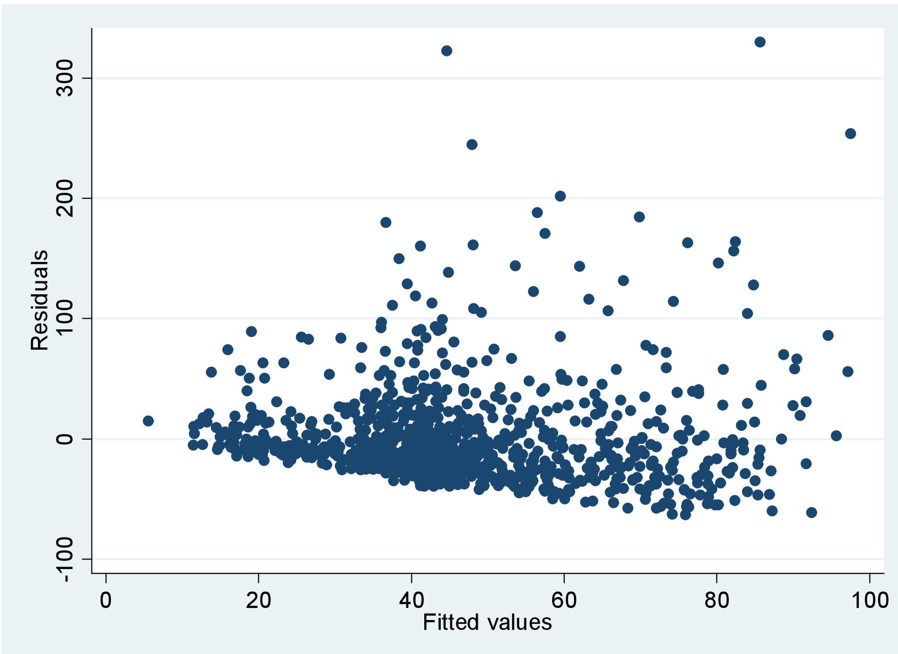
Appendix Figure A. Histograms of Teacher Quality Measures



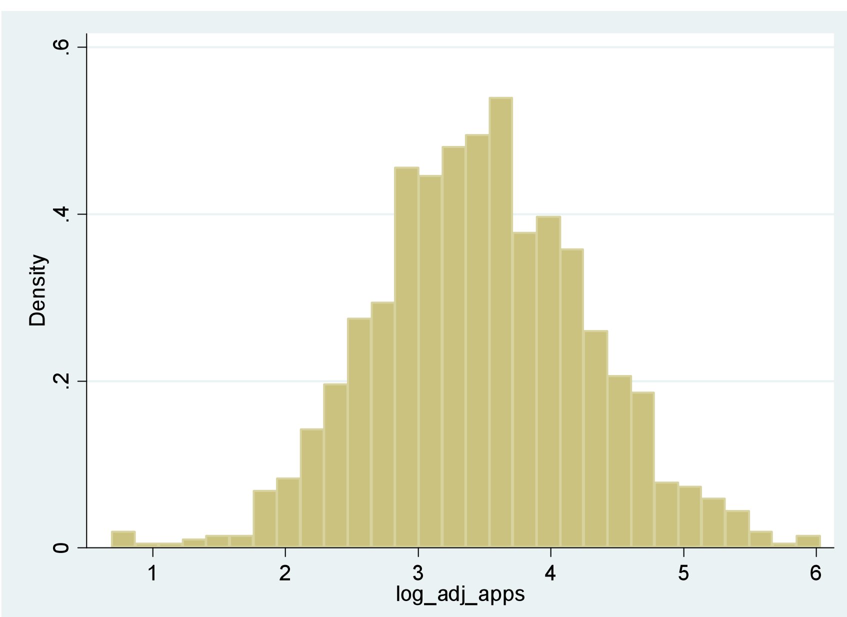
Appendix Figure B1a. Applicants per Vacancy (School-Level)



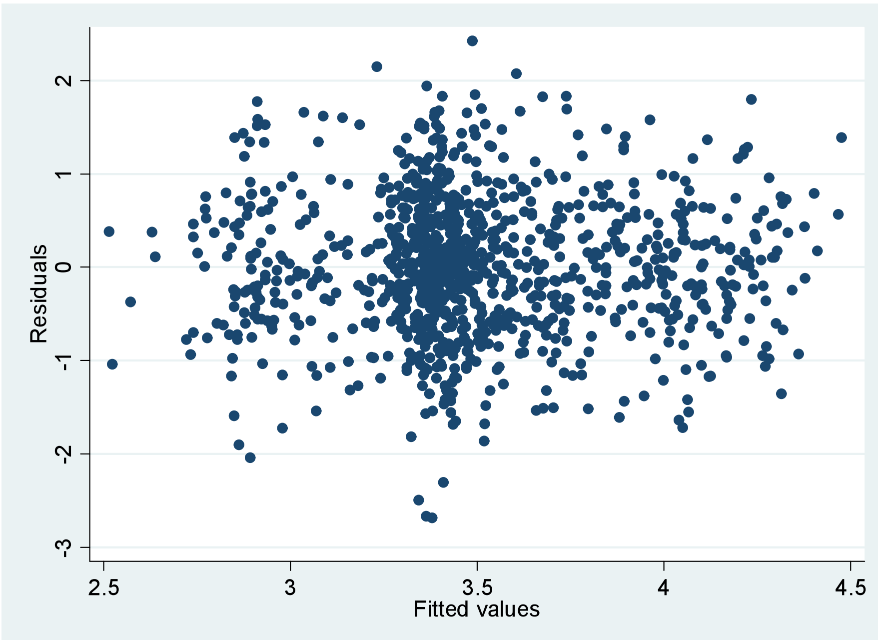
Appendix Figure B1b. Residuals from Multivariate Model for Applicants per Vacancy (School-Level)



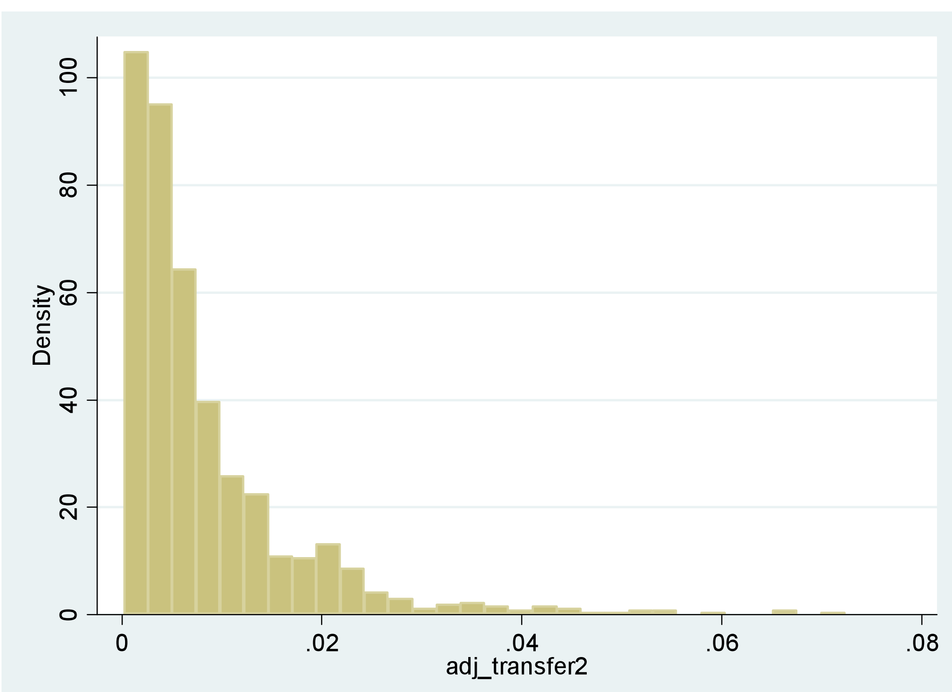
Appendix Figure B2a. Log (Applications per Vacancy), School-Level



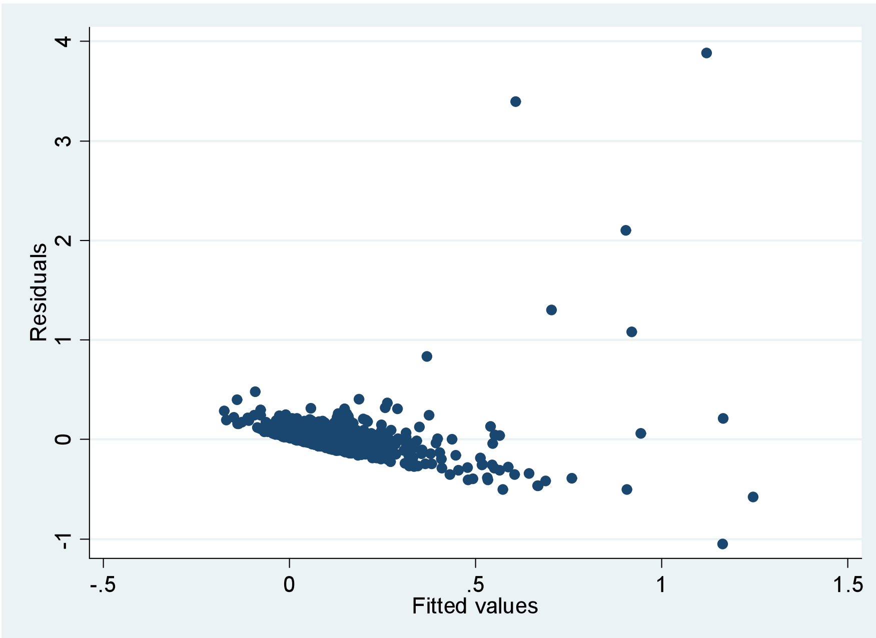
Appendix Figure B2b. Residuals from Multivariate Model for Log (Applications per Vacancy), School-Level



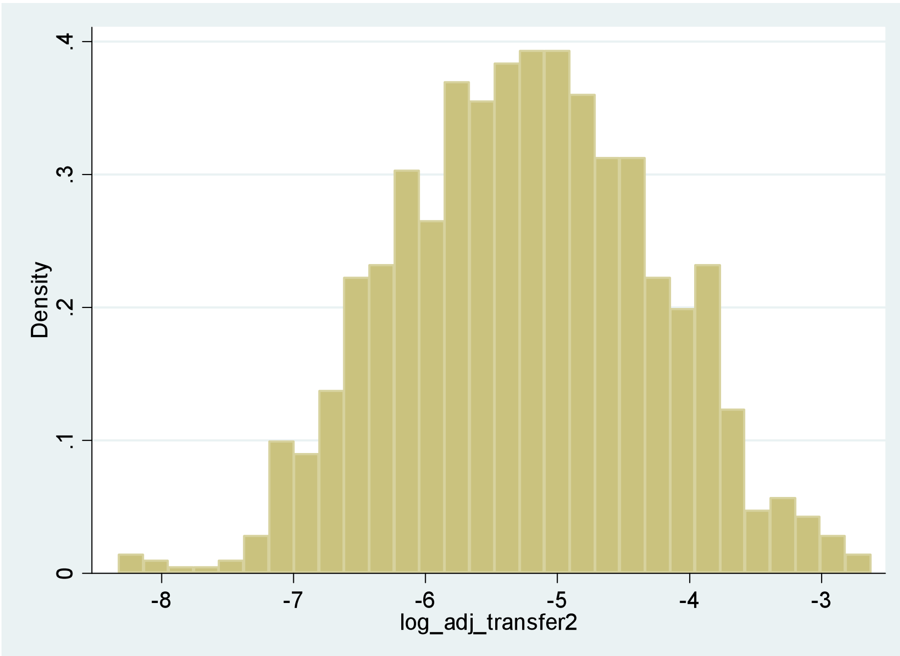
Appendix Figure B3a. Transfers per Student (School-Level)



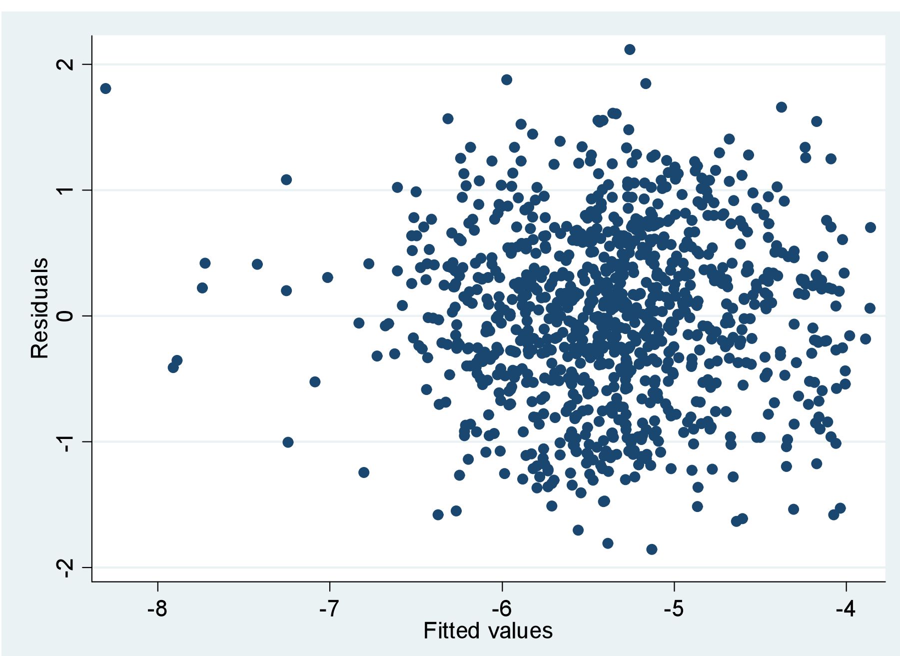
Appendix Figure B3b. Residuals from Multivariate Model for Transfer Requests per Student (School-Level)



Appendix Figure B4a. Log (Transfers per Student), School-Level



Appendix Figure B4b. Residuals from Multivariate Model for Log (Transfer Requests per Student), School-Level



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[i] The authors measure teacher effectiveness as the teacher's value-added contributions towards student achievement on standardized tests.

[ii] In related research, Boyd et al. (2009) employ a matching model to estimate the preferences of school hiring authorities and prospective teachers for the initial match of teachers to schools. They find that employers generally value teacher quality as measured by credentials and teachers value salary and school working conditions, including distance from their home.

[iii] We know if a teacher was hired, but do not know who else may have received a job offer for the same position. In terms of estimating school preferences for teachers, we would prefer to know all teachers who received job offers.

[iv] Boyd et al. (2005) provide more detail on the sources of this data.

[v] By "active" we mean teachers that are in the human resources database as paid regular teachers at the beginning of the school year who are working at 70 percent of full-time or more. Teachers who had taken leave, quit, or were of unknown status were dropped from our sample. Though teachers who quit or were on leave, for instance, make up some of the teachers who entered the Transfer Request System, there were relatively few. It did not make sense to include these teachers because we were interested in accounting for the effects of teachers' current school workplaces on their applying and transferring behaviors, often with school fixed-effects. Given these teachers were not currently in schools, such models could not apply. Our sample includes teachers who taught in NYC classrooms during either or both of the 2006–2007 and 2007–2008 academic years. In 2006–2007 there were 72,323 teachers in our sample. Most of these teachers were still active in NYC classrooms in 2007–2008, though some left teaching or left the state. Still other teachers entered teaching or the district in the second year of our study, resulting in 73,370 active teachers in our 2007–2008 sample. Altogether, 80,898 teachers were active in NYC classrooms in either or both academic years we studied.

[vi] Of active teachers, 9.7 percent became appliers in 2006–2007 and 8.0 percent became appliers in 2007–2008.

[vii] Beginning in the fall of 2003, new temporary license (uncertified) teachers were permitted only in extraordinary circumstances. However, a large number of teachers who had previously entered the system as uncertified remain, having since acquired certification.

[viii] We use the beginning-of-year placement in both academic years to estimate current school placement for a given year.

[ix] The specifics of these models and results are available upon request from the authors.

[x] Our main analyses focus on value-added to student achievement in math. However, we also ran models with a measure for teacher effectiveness that uses value-added to student achievement in English Language Arts (ELA). Our results are similar, so we report primarily on the math value-added measure. In our results sections we note how results using the ELA value-added measure are similar and different. Student achievement was normalized to have a mean of zero and a standard deviation of one unit.

[xi] Prior to 2006, New York State administered examinations in mathematics and English language arts for grades 4 and 8. 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 IRT methods were used to convert raw scores (for example, number or percent of questions correctly answered) into scale scores. New York State began administering all the tests in 2006. For more detail on the tests, see CTB/McGraw-Hill (2006).

[xii] Appendix Figure A for the distribution of LAST score, years of experience, and teacher value-added scores.

[xiii] Because we have value-added data only on teachers in grades 4 through 8, we run many models without value-added as a predictor to utilize our full sample. Thus, we present summary statistics on schools in our full sample, which include all grade levels, and not just grades 4 through 8.

[xiv] We use logs because of the positive skew of these distributions. The coefficients can then be interpreted as approximate percent change. Appendix Figure B provides the distributions of the original variables and the transformed variables. School characteristics were based on school averages using administrative data over the years 2003 to 2006; crime and suspension data are based on school averages over 2000 to 2006 because of missing data on these measures. We also ran the "applicants away" analyses again, but after dropping schools that closed anytime during the 2 years that we have applications data. We were concerned because school closures would result in an unusually high percentage of teachers from a closing school into the Transfer Request System. Given that certain kinds of schools may be more likely to close—for example, underserved and under-performing—we worried this would bias our estimates. However, our results remained consistent even after dropping schools that closed during our timeframe. Although we do not present the results here, they are available upon request from the authors.

[xv] Results between Models 1 and 2 differ, in part, because they are looking at different samples of schools. Also, the proportion of lowest-achieving students is related to other predictors in our model. For example, schools with higher proportions of black students also typically have higher proportions of lowest-achieving students. Thus, including the proportion of lowest-achieving students in models may change the point estimates on the proportion of black students.

[xvi] Because we do not have college competitiveness data on our full sample, we run Model 1 without college competitiveness as an indicator. As discussed previously, we have value-added data only on teachers in grades 4 through 8. Because we wanted to show results for our full sample in our other models, we include value-added as a quality indicator only in Model 6. We re-ran all models on the reduced sample of teachers for whom we have both value-added and college competitiveness data and got similar results. These models are available upon request from the authors.

[xvii] When using teachers' value-added to student achievement in ELA instead of math, we find that teachers with higher value-added scores are still less likely to apply for transfer, though the point estimates are smaller in magnitude and only moderately significant.

[xviii] We do not present these results here, but they are available upon request from the authors.

[xix] See Appendix Table 2 for results after excessed teachers and closing schools were removed.

[xx] Feng (2009), for example, finds evidence that classroom characteristics, like disciplinary incidents, indeed may influence teacher mobility.

[xxi] We did look at descriptive statistics on those teachers we had identified and removed as excessed for reasons other than school closure. Compared to all active teachers in NYC, there were higher proportions of male, older, and black teachers. A higher proportion of excessed teachers were also from temporary license and "other" paths. They had lower LAST scores and were less likely to come from competitive undergraduate colleges. However, their average experience and value-added scores were almost identical.

[xxii] As discussed previously, we have value-added data only on teachers in grades 4 through 8. We also have data on college competitiveness for a subset of our full sample. Because we want to estimate the effects of our other predictors on our full sample, Model 1 does not include value-added or college competitiveness. Model 2 includes college competitiveness and Model 3 includes value-added. We re-ran all three models on our constrained sample of teachers for whom we have both value-added and college competitiveness data and got similar results. These models are available upon request from the authors.

[xxiii] Here we report teacher effectiveness using teachers' value-added to student achievement in math. However, we find that the results are similar when using teachers' value-added to student achievement in ELA. The point estimate on teacher effectiveness in ELA is still positive and statistically significant, though smaller in magnitude—an increase of 1 standard deviation increases the likelihood of being hired by about 10 percent (in ELA) instead of 20 percent (in math).

[xxiv] We re-ran these estimates using two other approaches. In one case, we added school fixed-effects on the schools *from* which teachers applied for transfer in addition to school fixed-effects on the schools *to* which they applied. In another case, we controlled for various school features of teachers' current placements while still including fixed-effects on the schools to which they applied. The size and significance levels of estimates in both cases were consistent with models presented here in Table 10. We do not present these models but they are available upon request from the authors.

[xxv] Because we do not have college competitiveness data on our full sample, we run Model 1 without college competitiveness as an indicator. As discussed previously, we have value-added data only on teachers in grades 3 through 8. Because we wanted to show results for our full sample in our other models, we include value-added as a

quality indicator only in Model 6. We re-ran all models on teachers for whom we have both value-added and college competitiveness data and got similar results. These models are available upon request from the authors.

[xxvi] These results are consistent with prior work in the direction of the effect, though other studies have found the effect on teacher effectiveness to be statistically significant. One possible explanation is that here we are considering only 2 years of data. By contrast, Boyd et al. (2007) looked across a 6 year period and focused on new teachers. They found that the effect is particularly strong for first year teachers. Because the effect likely diminishes with experience, the non-significant estimate in this current study may also reflect that we include teachers across the experience spectrum.

[xxvii] The estimates of the effect of race in our work-history analyses are in the same direction as prior work (that is, black and Hispanic teachers are less likely to transfer), but the estimates are non-significant. One possible reason for why our estimates are non-significant may be that we have limited our focus to teacher transfer, while much of the prior work looks at turnover more generally (including both transfer and attrition).