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Staffing a Low-Performing School: Behavioral Responses to Selective Teacher Transfer Incentives

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ABSTRACT

In this paper, we examine behavioral responses to an incentive program that offers high-performing teachers in ten school districts across the country $20,000 to transfer into the district's hardest-to-staff schools. We discuss behavioral responses to the program on both the supply and demand sides—specifically, high-performing teachers' willingness to transfer (supply) and the effect of the transfer offer on the internal dynamics of receiving schools (demand). Internal dynamics include the assignment of students to teachers, assignment of teachers to grades, mentoring relationships, and teacher collaboration. We found low take-up rates among the 1,514 high-performing teachers who were offered the incentive, with minimal sorting on observable characteristics. Within the new schools, transfer teachers were less likely than their counterparts in a randomized control group to require mentoring and more likely to provide mentoring themselves. No significant differences occurred in school climate, collegiality, or the way in which students were assigned to teachers, but evidence indicates principals may have strategically assigned existing teachers to grades in both treatment and control schools in response to the quality of the incoming teachers.

I. INTRODUCTION

Recruitment incentives are increasingly proposed as a way to attract top teaching talent to low-achieving schools. Between 2006 and 2012, the U.S. Department of Education appropriated nearly $1.3 billion to fund recruitment, retention, and performance incentives in disadvantaged schools through Teacher Incentive Fund grants. Twenty states now offer incentives to teach in targeted schools, and eight of them make the incentives conditional on the teachers' having certification from the National Board for Professional Teaching Standards (*Education Week* 2013).[1] The success of such policies, however, depends on whether high-performing teachers can be induced to move into such schools and how the schools themselves would respond to the opportunity to bring in more talented recruits and take advantage of their skills and experience.

What we know about transfer behavior is largely based on mobility under normal circumstances, in the absence of policy initiatives designed to encourage teachers to move to targeted schools. This research indicates that, on average, teachers tend to transfer *out* of schools with higher proportions of minority and disadvantaged students (Feng and Sass 2011; Goldhaber, Gross, and Player 2011; Hanushek, Kain, and Rivkin 2004; Ladd 2011). Heterogeneity in teachers' responses to school context is substantial (Boyd et al. 2005), and teacher quality correlates highly with transfer decisions. Generally, more effective teachers are less likely than others to transfer within their districts (Goldhaber, Gross, and Player 2011; Boyd et al. 2011).[2] The findings are nuanced, however, and two studies based on Florida data found the most and

[1] National Board certification is an advanced teaching credential that requires a lengthy application process and demonstration of mastery through a portfolio and other materials.

[2] Teacher effectiveness in the studies reviewed here is measured by value added, which represents the unique contribution a teacher makes to growth in student test scores.

least effective teachers more likely than those in the middle to leave their schools (Feng and Sass 2011; West and Chingos 2009).

Teacher race/ethnicity is another mediating factor. Some studies have found that minority teachers are less likely to transfer in general (Boyd et al. 2011; Ladd 2011), and the probability of their transferring actually decreases as the percentage of minority students in their schools increases (Feng 2009; Hanushek, Kain, and Rivkin 2004; Imazeki 2005). Working conditions are also important factors, with fewer teachers moving out of schools that have strong leadership (Ladd 2011; Ingersoll 2001) and better student behavior records (Ingersoll 2001).

Not surprisingly, studies have shown teacher mobility and retention decisions to be related to compensation as well (Hanushek, Kain, and Rivkin 2004; Imazeki 2005; Stockard and Lehman 2004; Kelly 2004; Lankford, Loeb, and Wyckoff 2002), but much of this research is based on *inter*-district transfers because that is where salary differentials typically exist. Salary may be even more important in hard-to-staff schools, where additional compensation may be needed to overcome less attractive working conditions (Milanowski et al. 2009). One recent study (Feng 2009) used Florida data to simulate the effect of salary on retention in different types of schools and estimated that teachers in hard-to-staff schools would need to be paid an additional $10,000 a year to be retained at the same rate as those in average schools.[3]

Little is known about *intra*-district transfer decisions in which teachers are offered additional compensation to teach in more challenging schools within their districts. Although

[3] Average self-reported base pay for transfer candidates in our study was about $50,000, so this incentive represents approximately 20 percent of annual salary.

Clotfelter et al. (2006b) found that bonuses designed to retain teachers in disadvantaged schools in North Carolina reduced turnover, targeted recruitment incentives for disadvantaged schools in Massachusetts and South Carolina were less effective at attracting teachers (Fowler 2003; Southeast Center for Teaching Quality 2003). These mixed findings may be due to the different challenges associated with, respectively, recruiting teachers and retaining them, although one recent study indicated the latter was actually more difficult than the former in so-called hard-to-staff schools (Opfer 2011).

The current paper makes an important contribution to the literature on intra-district teacher transfers by examining the behavioral responses of teachers and principals to a selective teacher transfer program known as the Talent Transfer Initiative (TTI). TTI was designed to provide incentives for a school district's highest-performing teachers to transfer to its lowest-achieving schools and stay there for two years. This program is characterized by mutual consent, meaning program staff and district officials do not compel teachers to transfer, nor do they compel principals to accept transfers. Instead, program staff identify the high performers and the eligible receiving schools, offer the $20,000 incentive, and facilitate interviews. Thus, TTI mimics potential real-life transfer incentive policies, and the behavioral responses of the high-performing teachers and the receiving school principals shed light on the potential responses of both the supply and the demand sides of the teacher labor market within districts to transfer incentive policies like TTI.

In addition to examining the transfer process that occurred in TTI districts, we used an experimental design to examine the short-term impacts of the transfer program on dynamics within participating schools. One way school dynamics might be affected is through peer

collaboration and mentoring. Research indicates teachers are influenced by those around them, and a change in the composition of the teaching staff may affect both school dynamics and student outcomes. Several studies of teacher peer effects have found some spillover among same-subject teachers and perhaps even across subjects. Jackson and Bruegmann (2009) found that elementary teachers surrounded by high value-added peers performed better than those whose peers were lower performing.[4]

School dynamics may also be affected by principals strategically assigning teachers to grades and courses differently than they would under normal circumstances. Intra-school mobility is common practice and, in most cases, decided upon voluntarily by teachers or principals (Jacob and Rockoff 2011). The principals and, sometimes, teams of teachers take into account information about student achievement, student behavior, and teacher traits in making classroom assignments (Kraemer et al. 2012; Cohen-Vogel 2011). Some research shows assignment of teachers to students is not random, with more effective and experienced teachers tending to be assigned to higher-achieving students (Dieterle et al. 2012) and novice teachers to lower-achieving ones (Loeb, Kalogrides, and Béteille 2012; Feng 2010; Clotfelter, Ladd, and Vigdor 2006a).

The short-term impacts on school dynamics is a critical component in understanding the ultimate impact of TTI on student achievement and teacher retention. A companion paper (Glazerman et al. 2013) focuses on the impact of TTI on student test scores and teacher retention

[4] At the high school level, Koedel (2009) found the quality of math teachers within a school may have an effect on reading scores; however, some of the effect may be due to nonrandom student sorting.

over time. We find that in classrooms targeted by TTI, elementary reading and math scores were 10 to 25 percent of a standard deviation higher than test scores of students taught by teachers in the control group. There was no evidence of impacts in middle schools, but this could in part reflect differences between districts. Districts varied considerably in terms of impacts and in the distribution of elementary and middle school study teams. When we combined the elementary and middle school results, impacts on test scores for the whole sample were positive and were statistically significant in the second year after the transfer. We also found that TTI had a positive impact on teacher-retention rates while teachers were receiving bonus payments. After the incentives ended in the third year, 60 percent of treatment teachers who had filled study vacancies were still in their low-achieving schools, a survival rate that was higher than, but statistically not different from that of their control group counterparts. Given the positive impacts of TTI on student achievement and teacher retention, it is important to understand the context in which the intervention was implemented and the ways in which it affected schools, to inform future implementation of a similar program.

In this paper, we focus on how teachers responded to an opportunity to participate in TTI and how TTI affected school dynamics. In particular, we address the following research questions:

1. What were the **behavioral responses of teachers** to TTI? Specifically, what can we learn about the teacher recruitment process, who transfers, and where they transfer from?

2. What impact did the intervention have on the **dynamics within schools** that were offered the opportunity to participate in TTI? Specifically, how did TTI affect the allocation of resources, staffing patterns, assignment of students to teachers, and school climate?

II. THE TALENT TRANSFER INITIATIVE

Implementing the Talent Transfer Initiative involved identifying high-performing candidates to transfer, identifying potential sending and receiving schools, facilitating the transfer process, and supporting teachers after they transferred to new schools. The intervention was implemented within each of the ten participating districts (Section III includes a description of the study sample). Prior to implementing the full-scale intervention, we conducted a feasibility study as well as a pilot study within one district. We also solicited input on the intervention design from a panel of experts in the field as well as from TNTP, the organization that led implementation.

Identifying High-Performing Teachers Before the Transfer Process

The first step of the intervention is to conduct a value-added analysis of student test scores to identify the highest-performing teachers eligible for transfer. Value-added measures seek to describe the contribution teachers make to growth in student achievement, holding constant factors outside the teachers' control, such as student background and prior learning (McCaffrey et al. 2004; Lipscomb et al. 2010). We estimated value-added scores for teachers in seven of the ten districts in our study. Our approach was to estimate a teacher fixed effect from a regression of post-test score on pre-test (score from the prior year), student background characteristics, and grade-by-year dummy variables. Student background variables included dummies for race/ethnicity, special education status, English language learner status, whether over age for grade, and family income proxied by eligibility for free or reduced price lunch (FRL). Teacher

effects were estimated from a dosage variable that captured the percentage of the year each student was taught by each teacher. We used Empirical Bayes (EB) shrinkage to avoid the problem that teachers with less precisely estimated value added would be over-represented in the tails of the (unadjusted) value added distribution. EB shrinkage is a procedure whereby the teacher's estimated performance is a weighted average of the point estimate generated from the model and the mean performance for all teachers, where the weights are inversely proportional to the variance of the teacher effect estimate. Thus, teachers with imprecisely estimated performance—for example, if they taught very few students—would be pulled in further towards the mean and less likely to appear "highest-performing" by chance compared to teachers with more precisely estimated performance.

The other three districts were already using the Education Value-Added Assessment System (EVAAS), developed by the SAS Institute, and they provided us with the estimated value-added scores of teachers or the names of the high-performing teachers based on their estimates.[5] EVAAS scores are similar to the value added estimates generated by Mathematica, except they use more years of lagged test score data to predict future performance and they do not include student background variables as controls.

We used data from both EVAAS and our own estimates and we ranked all teachers with at least two subject-year estimates. Teachers in the top 20 percent of the value-added distribution in their districts, grade spans, and subjects were deemed "highest performing."[6] They

[5] Details of our value-added model can be found in Appendix B of Glazerman et al. (2012), and details of the methods used by the SAS Institute are provided at http://www.sas.com/govedu/edu/k12/evaas/index.html.

were estimated to have contributed 13 percent of a standard deviation more to student reading achievement and 23 percent of a standard deviation more to math achievement in a year than the average teacher in the district.[7]

Identifying Potential Receiving and Sending Schools

Schools in each district were classified as either "potential receiving" or "potential sending" schools. Potential receiving schools were those with the lowest achievement in their districts and which the district leaders intended to help through the intervention. Selected teaching positions in these schools, or "vacancies," were eligible for the transfer incentive. Across all ten districts, 21 percent of the schools were classified as potential receiving schools. The rest, with rare exceptions for special schools that are excluded from the intervention, were potential sending schools.[8]

Consistent with the program design, potential receiving schools were more disadvantaged than potential sending schools. We used the percentage of FRL students as a measure of disadvantage. In elementary receiving schools, 70 percent of students on average were FRL eligible, compared to 55 percent in elementary sending schools, a statistically significant

(continued)

[6] The cutoff for a teacher to be deemed "highest performing" in a district was typically 20 percent, which usually would generate a pool large enough to fill the target number of vacancies. The cutoff varied, however, across districts and grade span/subject pools (middle school math teachers, middle school English/language arts teachers, and elementary multiple-subject teachers) to be more selective or to enlarge the pool of candidates slightly. It was decreased to 18 percent for elementary teachers in two districts and increased to 25 percent for middle school teachers in another. Another district set the cutoff for middle school at 23 percent for math teachers.

[7] Scores are expressed in terms of standard deviations relative to the district-wide test-taking population for the given grade span and subject.

[8] Across all ten districts, 72 percent of schools were potential sending schools. The remaining 7 percent were exempt because they served special populations of students or were already implementing similar programs.

difference of 25 percentage points. For middle schools, the difference was also statistically significant, at 18 percentage points (79 percent versus 61 percent).

The Transfer Process

The highest-performing teachers at potential sending schools, whom we refer to as transfer candidates, were eligible to apply for transfer into vacancies in receiving schools through TTI. During the spring recruitment process, these teachers were offered a series of incentive payments, totaling $20,000 over two years, to transfer into and remain in one of the receiving schools in their districts. In addition, the TTI program implementation relied on extensive outreach by site managers from the implementation team, who served as a single point of contact for teacher candidates in each district and conducted three main recruitment activities: sending invitation letters, organizing a reception that also served as an information session, and maintaining frequent communication with teacher candidates to solicit their participation and invite them to apply and interview for specific openings.

Site managers contacted TTI candidates by email or phone at each step in the recruitment process: after sending the initial invitation letter, following the information session, as vacancies became available, and after teachers attended interviews. Where necessary (in two of the ten districts), a second information session was offered to increase the number of applicants. Conference calls were offered to answer questions posed by candidates. Teachers who did not apply to the program received ongoing communication from site managers about vacancies available through the program. Site managers typically targeted recruitment based on the grade level or subject area a teacher wanted to teach or teachers' geographic proximity to eligible

vacancies. For districts that had delays in identifying eligible vacancies, teachers received update emails to inform them about the status of the process.

District leaders also played an important role in recruitment. The district superintendent or human resources manager signed the initial invitation letter and attended the teacher reception to express the district's support for the program. At the reception, district staff typically discussed why the program was important and explained how it fit with existing district initiatives. Where necessary, the human resources staff sent additional emails urging unresponsive teacher candidates to apply to the program and informing them of the status of transfer opportunities at various stages.

At the same time that the transfer candidates were identified and contacted, principals of potential receiving schools were asked to identify teaching vacancies in targeted grades (3–8) and subjects (math, reading, or self-contained) that would be eligible for the transfer incentive. In each district, a site manager from the implementation team assisted in matching transfer candidates to principals and arranging interviews.

Not every potential receiving school had a teacher transfer into it, and not every potential sending school lost a teacher. For a potential receiving school to become a receiving school, its principal first had to voluntarily submit at least one vacancy for randomization; it had to have been assigned by the researchers to the treatment group; and at least one eligible TTI candidate had to have applied to, interviewed at, and successfully transferred to the vacant position. Across the ten districts, teachers who transferred through TTI came from 10 percent (68 out of 692) of potential sending schools. This percentage is relevant for districts concerned that a transfer

program like TTI may be disruptive to many of its sending schools. In fact, 90 percent of the schools identified as potential sending schools did not lose a single teacher. Those that did lose teachers were minimally affected, losing, on average, 1.2 teachers. If TTI were to be scaled up, with more positions targeted, the potential for sending schools to be affected would be greater.

Support Provided After the Transfer

TTI offered a half-day orientation to transfer teachers just before the start of the school year. To facilitate the transition, the site manager provided informal support and answered any questions as needed throughout the intervention period. During that time, teachers who remained in their originally assigned positions received incentive payments at the end of each semester, in December and June.

Teachers in the highest-performing group who were already teaching in low-performing schools (potential receiving schools) were not eligible to transfer under the program. Instead, they automatically qualified for a retention bonus of $10,000, also paid in installments over two years, as long as they remained in their schools. These teachers were not part of this study.

III. STUDY DESIGN AND SAMPLE

To estimate the impact of selective transfer incentives on participating schools, we implemented a randomized controlled trial.

Random Assignment

Through a random assignment process, “teacher teams” in low-achieving schools (potential receiving schools) were assigned either to a treatment group that could fill a vacancy through TTI or a control group that would fill vacancies the way they normally would in the absence of

the program. The unit of randomization was teacher teams, each of which was composed of all the regular classroom teachers in a given grade level and subject within a school. Once having identified teacher teams with vacancies, we matched them with teacher teams with vacancies at the same grade level (and subject, in the case of middle school teams) but in different schools. These matched teacher teams formed blocks, and we randomly assigned teacher teams within each block to the treatment and control groups.[9]

Each teacher team included the teacher who filled the vacancy, as well as his or her grade-level colleagues at the same school. We expected much of the impact of TTI to operate through the teachers who filled the vacancies in the treatment and control teacher teams; we refer to them as "focal" teachers. In addition to the team-level analysis, we were interested in the comparison between focal treatment and focal control teachers.[10] We refer to the other teachers on the teams as "nonfocal" teachers.

Sample

This paper focuses on ten large and economically diverse districts, seven of which began implementing TTI in 2009–10 (cohort 1 districts), and three of which began implementing in 2010-11 (cohort 2 districts). We selected districts that had at least 40 elementary schools, at least 10 of which were low-poverty schools and at least 15 of which were high-poverty schools. Low- and high-poverty schools were defined as having, respectively, fewer than 40 percent or more than 70 percent of students eligible for FRL. In addition to these quantitative criteria, we selected

[9] Random assignment occurred after principals voluntarily submitted vacancies (consented).

[10] See Appendix A for a description of how the focal teachers were identified and included in the analysis.

districts on the basis of a variety of qualitative factors related to feasibility of implementation, including test score availability, data quality, hiring/transfer practices, and the local political environment. Thus, the districts included in this study are only representative of similar school districts in the country.

The ten districts in the sample were in seven states. Six of the ten districts were county districts, including urban centers as well as suburban and rural areas. The districts ranged in size from 55 to 218 elementary and middle schools. Hispanic students made up the majority of students in four of the districts, and African American students were the majority in one. Another district had a majority white student body, and the remaining four were without a majority of any one racial or ethnic group (Hispanic, African American, white, or other).

In all, the study included 700 teachers in 165 teacher teams in 114 participating schools. Eighty percent of the teachers were in elementary schools (grades 3–5) and the other 20 percent in middle schools (grades 6–8).[11] Sixty-four schools included at least one team that was assigned to the treatment group and had hired a TTI teacher, 9 included at least one treatment team that chose not to fill the study vacancy with a TTI teacher,[12] and 41 included only control teams. There were 85 treatment teams and 80 control teams.[13]

[11] There were 180 vacancies in 165 teacher teams because 13 teams had 2 vacancies each, and one had 3 vacancies. In the treatment group, 7 teams had 2 vacancies, and no teams had more than 2.

[12] A team remained in the study if a vacancy was submitted and randomly assigned, even if no teachers transferred to that school.

[13] The number of treatment and control teams was unequal because teams were not always randomly assigned in pairs; some were assigned in groups of three. Because randomization occurred on a rolling basis as vacancies opened, some teams were randomly assigned without matches because no comparable vacancies were available within the district at the time of randomization.

We compared pre-test scores and demographic characteristics of students from treatment and control teams for the math and reading analysis samples (Table 1). Although teams were randomized to treatment or control group status, there were significant differences between the groups on some background characteristics, including the percentage of students who were African American, English language learners, and eligible for Free or Reduced Priced Lunch. However, the only significant difference in pre-test scores occurred in the reading sample for students' opposite-subject pre-test scores—treatment students had higher math pre-test scores than control students. These differences between students on treatment and control teams are likely due to chance, since circumventing random assignment would necessitate that students systematically changed schools due to their random assignment status.[14]

[TABLE 1]

IV. METHODS AND DATA

This study addresses the research questions of interest with multiple methods, including descriptive statistics, multivariate regression analysis, and impact analysis. These analyses are conducted with data from several sources, including administrative, program, and survey data.

Methods

To answer the first research question—what was the behavioral response of transfer teachers to TTI?—we produced descriptive statistics on the rates at which teachers applied and

[14] Chance differences are feasible with this study's random assignment design because demographic characteristics varied considerably between schools but did not vary much within schools. We adjust for these chance differences in our impact analyses (Glazerman et al. 2013).

transferred through TTI. We also conducted a multivariate regression analysis to examine which of their characteristics and survey responses were correlated with their decisions to apply and transfer.

To answer the second research question—what was the impact of TTI on school dynamics?—we used data from the randomized controlled trial described above. We analyzed survey and administrative data for treatment and control teams, which differed only in their opportunity to hire TTI teachers, to estimate the impact of the intervention on school dynamics. Thus, we could infer that such differences were caused by the incentive program.

Data

The data for the study came from administrative records and survey results, as well as from program implementation records. We collected several types of administrative data from the school districts, including student test scores linked to teachers, student demographic data, and teacher rosters. We also conducted surveys in the winter and spring of the 2009–10 school year (cohort 1) and the 2010-11 school year (cohort 2) with three groups: (1) all teachers who had been identified as high performing and hence eligible to transfer, referred to as candidates (candidate survey); (2) all teachers (focal and nonfocal) on treatment and control study teams (teacher background survey); and (3) all principals of schools with study teams (principal survey). Details on data sources and response rates can be found in Appendix B.

V. FINDINGS: BEHAVIORAL RESPONSE OF TEACHERS

We addressed the study's first research question regarding the behavioral response of teachers to TTI by analyzing data on the application and transfer processes and results. The

findings described in this section relate to the extent to which teachers voluntarily participated in the transfer initiative, which teachers participated, where they transferred from, and how they differed from the teachers that would normally have filled the vacancies.

Teacher Take-Up Rates

To gauge the response of the TTI candidates to the offer of a transfer incentive, we examined the rates at which they took part in various phases of the process ("take-up rates"), from attending information sessions to completing applications, interviewing, and ultimately transferring. Figure 1 presents the take-up rates by grade span and subject based on TTI program records.

Most teachers who were offered the transfer incentive did not apply or even attend an information session. Only 32 percent of the eligible candidates attended an information session, after which 69 percent of attendees completed the one-page online application form. Application rates as a percentage of all candidates (including those who did not attend the information session) ranged from 17 to 26 percent, with a higher percentage of elementary than middle school teachers applying. All the high-performing TTI teacher candidates received a letter from their districts, which congratulated them on being identified as a high-performing teacher, notified them about their candidacy for TTI, and invited them to the information session. The implementation team also contacted the teachers and encouraged them to attend the information session and apply for the program. Given these extensive outreach activities, the low take-up rates likely represent weak interest among high-performing TTI teacher candidates in transferring to lower-achieving schools rather than insufficient dissemination of information about the program.

[FIGURE 1]

Of those who expressed initial interest by applying for TTI positions, a majority followed through to the interview stage. Fifty-five percent (12 percent of all candidates) interviewed for at least one vacancy. The other 45 percent who applied either did not follow through or were not given a chance to interview. Unlike the low rates of information session attendance and application, which likely reflect lack of interests among the high-performing teachers, low interview rates could result from either a lack of interest on part of the teachers to interview for the particular low-achieving schools with vacancies or from receiving school principals being too selective or both.

Data on interviews, offers, and acceptances that we obtained from the site managers provide some insight into the selectivity of the hiring process. Among the 174 candidates (12 percent of 1,514) who interviewed for at least one of the 92 available TTI vacancies, there were a total of 288 interviews because some candidates interviewed for more than one position.[15] Thus, the average number of interviews per TTI vacancy was about 3.1. Offers were made to 97 candidates; of them, 10 received two or more offers.[16] In total, 109 offers were made by TTI schools to fill the 92 TTI vacancies, or 1.2 offers per TTI vacancy and 0.4 per candidate interviewed. This means that most principals with treatment teams made offers to only one TTI

[15] Candidate Survey data suggest that of those who did interview, 104 teachers (60 percent) interviewed at one school, 40 (23 percent) interviewed at two schools, and the remaining 30 (17 percent) interviewed at three or more schools.

[16] The number of offers received is self-reported by candidates in the Candidate Survey.

candidate and to one of three they interviewed.[17] It is interesting to note that the hiring pattern did not differ between treatment and control teams. We used the Principal Survey to examine hiring rates as reported by the principals of both teams and found no statistically significant differences in the numbers of applicants considered, applicants interviewed, offers made, or acceptance rate faced by the principals (Table 2).

[TABLE 2]

Determinants of Application and Transfer Behavior

We examined the demographic, residential, and professional characteristics of candidates by their application status to better understand the influence of their observable background characteristics in their career choices. In Table 3, we present a descriptive comparison of characteristics between those who did not apply, those who applied but did not transfer, and those who transferred. Because many of the candidate characteristics listed above are related to one another, we performed multivariate analyses to understand which factors correlate with candidates' decisions to apply and transfer.

[TABLE 3]

We estimated a logistic regression model to determine whether the demographic, residential, and professional characteristics of candidates correlated with their decisions to apply for TTI positions and transfer. First we modeled the decision to apply and then repeated the analysis

[17] However, principals in TTI schools could have made offers to candidates who were not TTI candidates. Unfortunately, we do not have information regarding this.

using transfer status (whether a candidate transferred or not) as the outcome, conditional on having applied. We used the following logistic regression to determine which factors were statistically related to the probability of a candidate applying:

$$Logit(\Pr(Y_{id}=1)) = \alpha + \beta_1 I_{id} + \beta_2 X_{id}^{b} + \beta_3 X_{id}^{r} + \beta_4 X_{id}^{p} + \beta_5 S_{id} + \delta_d + \varepsilon_{id} \quad (1)$$

The dependent variable, Y_{id}, is an indicator of whether candidate *i* in district *d* applied or transferred. The explanatory variables included in the regression model are (1) a measure of income, *I*, of the candidate, which is the base salary plus any compensation; (2) a vector of personal characteristics, X_{id}^{b}, of the candidate, including gender, race, an indicator for whether the candidate is married and has co-residing children under age 5, an indicator for whether the candidate is married and has co-residing children over age 5, and an indicator for whether the candidate is unmarried;[18] (3) a vector of residential characteristics, X_{id}^{r}, including whether the candidate owns a home and average commute time from home to current school; (4) a vector of professional characteristics, X_{id}^{p}, including two indicators denoting the competitiveness of the candidate's undergraduate institution,[19] candidate's degree, and National Board certification status; and (5) a set of indicator variables summarizing the candidate's satisfaction with different aspects of his or her current school, S_{id}, including school leadership/policy, payments and

[18] The omitted category is married candidates without children. These four categories jointly represent the entire sample; we do not have any unmarried candidates with children in our sample.

[19] Competitiveness of undergraduate institution is based on Barron's Profiles of American Colleges (2003). We used two indicators—the very competitive indicator takes a value of one if the candidate's undergraduate institution is one of those listed as "most" or "highly" or "very competitive" and the competitive indicator takes a value of one if the candidate's undergraduate institution is "competitive." According to Barron's profiles, a "very competitive" undergraduate institution is one that admits less than 75 percent of applicants and whose students were ranked at least in the top 35 to 50 percent in high school. The omitted category is "not competitive."

benefits, professional environment, school environment and facility, and students.[20] We also accounted for district fixed effects, δ_d, to account for any conditions at the district level that we did not observe but that could influence decisions of all candidates within districts similarly, such as district union policies or labor market conditions. Standard errors of estimated logit coefficients accounted for clustering at the school level, to account for the possibility of unmeasured factors common to the same potential sending school at which multiple candidates may teach.

Teachers who applied to TTI were different from those who did not apply in some consistent ways. Table 4 presents the average marginal effects of teacher characteristics from the specification in equation (1) on the probability of applying.[21] As can be seen from the results in Column 1, teachers who applied were more likely to have lower income, be African American, be unmarried, have attended a competitive undergraduate institution (compared to attending not competitive institutions), and be less satisfied with their current school policy and professional

[20] The indicator variables for satisfaction were constructed from a series of aspects of a candidate's current school for which the candidate chose his or her satisfaction level on a four-point Likert-type scale—very dissatisfied, somewhat dissatisfied, somewhat satisfied, and very satisfied. A candidate was assumed satisfied for an aspect if he or she were somewhat or very satisfied. Aspects were grouped in the survey questionnaire to reflect satisfaction with school leadership/policies, compensation, professional environment, school environment and facility, and students and their families. We also conducted factor analysis to confirm that the items (aspects) loaded into the five predefined categories. The dummy variables summarizing satisfaction with the five categories were constructed as follows: a candidate was defined as satisfied for a category and was given a value of one if he or she were satisfied with more than 50 percent of the aspects within that category and given a zero otherwise. We also constructed an alternative set of dummy variables using a more restrictive definition, wherein a candidate was defined as satisfied for a category if he or she were satisfied with all the aspects within it. Using this alternative set of dummy variables did not change the regression results, however.

[21] Each of the estimated coefficients of equation (1) from a logistic regression would represent the effect of a unit change in a particular explanatory variable on the log odds in favor of a teacher applying. For ease of interpretation, we calculated the marginal effects of a unit change in each explanatory variable on the probability of applying for each individual teacher given the regression coefficients and their characteristics. We then averaged the marginal effects across teachers for each explanatory variable to obtain the average marginal effects.

environment.[22] Married teachers with co-residing children under age 5 were also more likely to apply compared to married candidates without children. None of the other personal, professional, or residential characteristics were significant predictors of application.

[TABLE 4]

Next, we examined the probability of transferring for candidates who applied to the incentive program (Table 5, first column). Average marginal effects from this logit regression presented in Table 5 show that once the decision to apply was made, teachers who were African American, married and living with children of any age (compared to married teachers without children) were more likely to transfer than others. However, marginal effects of these factors were only significant at the 10 percent level. Other factors did help explain transfer decisions, however. Contrary to the hypothesized direction of the effect, transfer candidates who were satisfied with their current salary and students during the application period were 12-15 percent *more* likely to transfer than those who were not, a statistically significant relationship at the 5 percent level.

[TABLE 5]

Using the same multivariable approach discussed above, we next examined the probability of candidates' applying to TTI within the seven districts where we estimated value added; these

[22] In a different specification, we used base salary instead of income, and the results were the same. The correlation between base salary and income was 0.91. We also estimated alternative models using age or experience, which were correlated with each other and with salary. Separating the influences of these variables may therefore be difficult.

were the only districts with data available on student characteristics and value-added scores measured before candidate identification, recruitment, and transfer. To the explanatory variables already included in Equation 1, we added a variable indicating whether a candidate was in the top 10 percent (top decile) of his or her district value-added ranking, as opposed to the rest of the candidates, who were from the second decile. We also included the percentage of candidates' current students (at the time of the transfer decision) who were FRL eligible (Table 4, second column).[23] Our hypothesis is that the teachers who have a higher percentage of current students who are disadvantaged are more likely to apply or transfer, because the student composition in the schools that they will potentially transfer into is likely to be similar.

In these seven districts, unmarried candidates, married candidates with children under 5, and candidates with master's or higher degree were more likely to apply for TTI positions, although the marginal effects were only significant at the 10 percent level. Also more likely to apply were candidates with higher percentages of disadvantaged current students and candidates who were in the top 10 percent of value-added ranking—the best of the highest-performing teachers. On the contrary, teachers who are Hispanic, own home, and have national board certification are less likely to apply.

We found none of the background characteristics of the candidates from these seven districts were statistically significant predictors of transfers except for home ownership (Table 5, second column). Also, we found that teachers satisfied with their current salary, school facilities, and

[23] Percentage African American, percentage Hispanic, and percentage with limited English proficiency are three other measures of student disadvantage. We did not include these in the regression because of their high correlation with percentage FRL status, 0.30, 0.45 and 0.45, respectively.

students are more likely to transfer. The marginal effects of all of these variables are significant at the 10 percent level. Neither being in the top 10 percent of the teachers rated for value added nor having higher proportions of disadvantaged students measured by FRL status made candidates more likely to transfer.

Low-Contrast Transfers

The goal of an intervention like TTI is to help low-achieving schools by recruiting strong teachers from schools that are not low achieving. Some types of transfers may serve that goal better than others. In designing the intervention, all schools in each district had to be assigned to one of two groups: low achieving (potential receiving schools) or not low achieving (potential sending schools). Establishing a discrete and somewhat arbitrary dividing line in the distribution between the groups means it is possible for a teacher to transfer from a school just above the threshold to one just below it. We call these moves low-contrast transfers because the difference in achievement ranking between the sending and receiving schools is small. In these cases, the transfer incentive might be counterproductive if the sending school is itself in need of strong teachers and has difficulty filling the vacancy created by the transfer.

One way to address the question, “where do transfers come from?” was to compare the rankings of the sending schools left by the transfer teachers to those of the receiving schools to which they transferred. We grouped the transfers by the degree of contrast, measured as the difference in rank between the sending school and the receiving school for a given transfer. The maximum degree of contrast would be a transfer from the highest-achieving to the lowest-achieving school in the district, a difference of 100 percentile points.

We found that the transfers included a mixture of high, low, and moderate contrasts in terms of school achievement rank. The average transfer represented a change of 41 percentile points, from the 57th percentile school (with 100 percent being highest performing in the district) to the 17th percentile school. The distribution of transfers by type of contrast, grouped into four categories, is shown in Figure 2. We classified only 16 percent of transfers as low contrast, defined as fewer than 15 percentile ranks difference. More than half of the transfers were between schools that differed by 16 to 60 percentile ranks.

[FIGURE 2]

In terms of poverty (percentage FRL), the average transfer represented a change of 23 percentile points, from the 45th to the 21st percentile. The distribution of transfers by type of contrast is shown in Figure 3. When we used percentage FRL, a much larger proportion (42 percent) of transfers were low contrast, but the majority of moves still represented a change of more than 15 percentile ranks.

[FIGURE 3]

Another way to address the question was to compare the characteristics of the students taught by TTI transfer teachers in their sending schools before they transferred to those of the students in their receiving schools after they transferred. On average, we found statistically significant differences between students taught by TTI transfer teachers before and after the transfer. Table 6 shows the average student characteristics before and after transfer for the 52 transfer teachers from the seven districts for which we had detailed individual student data for both sending and receiving schools.

On average, TTI teachers moved to classrooms in the receiving schools with a lower percentage of white students than in the sending schools (9 percent versus 24 percent) and a higher percentage of low-income students, as measured by FRL eligibility (93 percent versus 68 percent). Test score differences between the transfer teachers' sending and receiving schools were also statistically significant for this group of teachers. On average, students in the transfer teachers' classrooms before the transfer scored 0.06 standard deviations below the district average in reading, placing them in the 48th percentile. The same teachers' students in the schools to which they transferred scored 0.39 standard deviations below the district average, placing them in the 35th percentile, a difference of 13 percentile points. The math scores of students taught by transfer teachers averaged 0.09 standard deviations below the district average (46th percentile) before the transfer and 0.38 standard deviations below average (35th percentile) in the schools to which they moved, a difference of 11 percentile points. Thus, by more than one metric, we see that transfer teachers, on average, come from schools with average performance slightly below district norms.[24]

[TABLE 6]

Transfer Outcomes: Teacher Characteristics Relative to Counterfactual

Understanding who filled the treatment vacancies offers another perspective on how teachers responded to the offer of a transfer incentive. The characteristics of teachers who filled the control vacancies help us understand the counterfactual—that is, who would have filled the

[24] Although sending schools had students who, by design, had higher average test scores than those in receiving schools, sending schools were not necessarily above average within the district. Sending schools are drawn from approximately the top 80 percent of schools in each district.

treatment vacancies in the absence of TTI. Both questions shed light on how the transfer incentive affected the composition of teaching staff at low-achieving schools. One might expect the treatment group vacancies to be filled by teachers identified through the TTI process, whereas the control group vacancies would be filled by hiring new teachers into the profession. In reality, vacancies could be and were filled through a variety of means. Although most control group vacancies were filled through new hires or transfers from other schools, several were filled by moving teachers from another grade or subject within the school—and, in some cases, the positions were lost altogether because of declining enrollment. At the same time, although most treatment group vacancies were, indeed, filled through TTI, some were filled outside the program.

Treatment vacancies. For the most part, vacancies assigned to the intervention were filled with TTI candidates. Eighty-one out of 92 positions (88 percent) had successful transfers. Of the eleven positions assigned to the treatment group that were not filled by TTI teachers, four were lost because of enrollment declines or because a teacher was recalled from a layoff notice that had created the vacancy; the remaining seven were simply unable or unwilling to find a match with TTI candidates, and the principal hired outside that pool instead.

Control vacancies. Before conducting the study, we hypothesized that many control vacancies would be filled by those entering the teaching profession, but some could be filled in other ways. Teachers might transfer from other schools, be hired away from other districts, or simply move from another grade level within the same school. In practice, control group vacancies were filled by a combination of new hires (19.3 percent), transfers in (21.6 percent), and within-school reassignments (29.5 percent). Other vacancies were filled by teachers of

unknown origin or were not filled due to enrollment changes, cancelled transfers, or rescinded layoffs. This breakdown illustrates the counterfactual—that is, what would have happened to teaching vacancies in low-achieving schools in the absence of TTI.

The teachers in the treatment group all had at least 2 years of experience and almost half (44.1 percent) had at least 11. The difference in experience level between treatment focal and control focal teachers (3.6 years) was statistically significant. Close to half of teachers who filled treatment vacancies held master's or doctoral degrees, and 20 percent were National Board certified (Table 7). Although 41 percent of teachers who filled the control group vacancies were new to the school, not all were new to the profession. In fact, a greater proportion (44.7 percent) reported being in at least their sixth year of teaching. Thirty-six percent held a master's degree, and 9 percent held National Board certification. The experience profile of these teachers reflects the fact that many were experienced teachers who simply moved from elsewhere in the school or district and were not hired out of the beginning teacher pool. Even so, control focal teachers had, on average, 3.6 fewer years of experience and were significantly less likely to hold National Board certification than treatment focal teachers (Table 7).

[TABLE 7]

VI. FINDINGS: BEHAVIORAL RESPONSE OF RECEIVING SCHOOLS

We addressed the study's second research question regarding the behavioral response of principals and teachers within receiving schools by comparing data on school dynamics after the transfer at treatment and control schools. To estimate the impact of the intervention on school dynamics, we analyzed how student assignment to teachers, teacher assignment to grades,

mentoring resource allocation, and teacher collaboration differed in the treatment and control groups.

Assignment of Students to Teachers

We hypothesized that a transfer incentive could change the way schools assign resources within the teacher team. For example, a principal might try to leverage the experience and skill of a transfer teacher by assigning that teacher more difficult students and assigning the less challenging students to the remaining teachers in the grade. Therefore, we sought to understand the relationship between students assigned to focal teachers and nonfocal teachers and to compare the focal/nonfocal difference between treatment and control teams.

We used three data sources to examine student assignment differentials: (1) administrative data on student characteristics, (2) principals' perceptions from the principal survey, and (3) teachers' perceptions from the teacher background survey. The administrative data provided objective information on a few easily observed traits. The teacher survey data were subjective, but they captured differences not only in demographic characteristics but also in students' behavioral challenges. The principal survey data were also subjective, but they allowed us to focus specifically on the assignment process and allow respondents to tell us directly how they intended to assign students.

The evidence regarding whether students were assigned differently to teachers as a result of TTI was mixed. When we compared the distribution of student characteristics in the focal teachers' classrooms to that of their nonfocal peers, we found no significant relationship between treatment status and characteristics of students assigned to the focal teachers relative to nonfocal teachers. To examine this relationship, we computed a difference-in-differences measure of

student assignment, δ. For any student characteristic, *Y*, the measure of student assignment, δ , is calculated as follows:

$$\delta = \left(Y_{focal} - Y_{nonfocal}\right)_{Treatment} - \left(Y_{focal} - Y_{nonfocal}\right)_{Control} \quad (2)$$

Because we were concerned that average difference in differences using equation (2) might mask the key phenomenon of interest (large positive or negative values, which could offset each other across teams in different schools), we created the first-differences (focal-nonfocal differences) as a categorical variable and conducted a chi-square test of the independence of first-differences from different treatment status (second-differences) across teacher teams.

As Table 8 shows, focal teachers on treatment and control teams were assigned students in a range of different ways, with some teaching lower-achieving students than those of nonfocal teachers, some teaching similar students, and some teaching higher-achieving students. We found a similar pattern for student disadvantage, measured by FRL, shown in Table 8 as well. We also examined the distribution of English language learners, students receiving special education services, and students belonging to certain race/ethnicity categories and found no evidence of differential student assignment on treatment and control teams for any of these characteristics either.

[TABLE 8]

The principal survey also revealed no statistically significant differences in the methods principals said they used to assign students to classrooms on treatment and control teams.

However, evidence supporting differential student assignment did emerge from teacher reports about whether their own students were more or less challenging than those of their peers. Focal teachers were more likely to report having more academically challenging students than their peers in treatment teams than in control teams. Forty-two percent of treatment focal teachers reported their students were more academically challenging than their peers, compared to 26 percent of control focal teachers (Figure 4).

[FIGURE 4]

Assignment of Teachers to Grades

Another way we hypothesized TTI might alter schools' internal dynamics was through resource allocation across grades rather than within them. In other words, where principals under the status quo (represented by control school teams) might compensate for weak incoming teachers by moving veterans who could mentor their less experienced colleagues from elsewhere in the school into their grade teams, principals in treatment schools might move weak teachers into the grades with the stronger incoming TTI teachers.

The limited evidence we had bore out this hypothesis, suggesting TTI did, indeed, have a resource allocation effect operating through assignment of teachers to grades. On the teacher background survey, we asked teachers to tell us about their prior-year assignments, which allowed us to identify within-school movers. We found 26 percent of treatment nonfocal teachers and 19 percent of control nonfocals had moved within their schools. When we compared the experience of those who moved into treatment teams in the first year of the program with that of those who moved into control teams (Table 9), we found control movers had, on average, 4.6 years more classroom teaching experience than treatment movers. The rates at which teachers

had National Board certifications were significantly different at the 10 percent level. Although 20 percent of control movers had this credential, only 6.3 percent of treatment movers did.

These differences indicate principals may have responded to TTI transfers differently than they would to typical new hires. Rather than moving their more experienced teachers into grades with new hires, they were free to place them in other grades and may, in fact, have moved weaker teachers into treatment grades to work alongside high-performing transfer teachers. The implication is that TTI may have effects on schools beyond the grades that receive the transfer teachers through the rearrangement of teachers across grades.

[TABLE 9]

Allocation of Mentoring Resources

Strategic assignment of students or teachers is one way principals might adapt to the opportunity to fill vacancies with transfer teachers in a program like TTI. Another is to shift mentoring resources that would have gone toward supporting new, presumably inexperienced teachers to other teachers, or perhaps to reduce the level of mentoring in that grade level altogether, freeing more resources for other grade-level teams in the same school or for other types of interventions in the same grade.

Mentoring received. To measure the extent to which mentoring resources were reallocated in response to incoming TTI teachers, we asked teachers to report on whether they had mentors, from whom they received mentoring, and how much time they spent with their mentors. Focal teachers in treatment teams received less mentoring than focal teachers in control teams. As shown in Figure 5, treatment focal teachers (comprising TTI transfers and whoever else filled the

targeted vacancies) reported having mentors at a significantly lower rate (39 percent) than did control focal teachers (59 percent). The time spent with a mentor per week on average was 35 minutes and 49 minutes, respectively, for treatment and control focal teachers. The peer teachers (nonfocal), both treatment and control, reported receiving levels of support in between that of treatment and control focal teachers: 45 percent of treatment peers and 47 percent of control peers had a mentor.

We did not find evidence that the impact on focal teachers was offset by an equivalent, opposite impact on nonfocal teachers, which would have happened if the resources were simply shifted within the team. Figure 5 also indicates TTI teachers reported receiving less mentoring from other teachers in the school than did their counterparts, suggesting that the reduced use of mentors by TTI teachers largely reflected a reduction in reliance on other teachers in the school.

[FIGURE 5]

Mentoring provided and other leadership roles. Yet another way for a school to take advantage of TTI teachers' expertise might be to assign them additional duties or responsibilities. The design of the intervention did not require principals to create any special duties or roles or require teachers to perform them as a condition of being hired or receiving the TTI bonus, but principals were not restricted from imposing such conditions or from simply assigning the teachers to, or requesting that teachers fill, such roles.

We found treatment focal teachers provided significantly more mentoring to their peers than did control focal teachers (24 minutes versus 6 minutes per week spent providing such assistance). Of the nonfocal teachers, 17 percent of treatment group teachers provided an average

of 22 minutes of mentoring per week, while 16 percent of control group teachers provided an average of 28 minutes per week. These differences for nonfocal teachers were not statistically significant, so evidence is insufficient to conclude that the amount of mentoring provided by the treatment focal teachers resulted in an offsetting decrease in the amount of mentoring provided by their peers. None of the treatment/control differences in the rates at which focal or nonfocal teachers played leadership roles were statistically significant.

Impact on Collaboration and Resource Allocation

One concern about an intervention that offers large stipends to teachers for having produced high value-added scores is that it may undermine collegiality and weaken collaboration and trust within the teaching team. Such phenomena are difficult to measure, but we posed a variety of questions to principals about these aspects of school climate. The principal survey asked respondents to rate each of their teaching teams from one to five on the level of collaboration, the extent to which teachers trust and mutually respect one another, and the extent to which teachers seek ideas from one another. They were then asked how this rating compared to the same dimension at the beginning of the school year and in the previous school year.

We did not find evidence of a breakdown of morale or any significant impacts on the way teachers worked together. No statistically significant impacts were found on principals' opinions of the degree of collaboration, trust, and sharing of ideas within grade teams. Treatment/control differences in the principals' ratings of teacher teams were not statistically significant for the three dimensions of school climate: collaboration, trust and mutual respect, and sharing ideas among teachers.

VII. DISCUSSION

Despite the growing policy focus on selective incentives to attract teachers to hard-to-staff schools, little is known about how teachers and schools respond to such programs. This paper has offered evidence from a randomized controlled trial in ten large districts. We found that vacancies in low-achieving, disadvantaged schools could be filled with a district's highest-performing teachers by offering a $20,000 transfer and retention incentive. Because many teachers were not interested in transferring, however, we needed a large initial pool of high-performing teachers to fill the study vacancies. Although some of the low take-up rates may have been due to hiring decisions by principals, it is telling that less than one-quarter of eligible candidates even applied for the program. An important implication of this finding is that scaling up a program such as TTI could be very difficult, as we mention below.

We learned that those who did apply to transfer differed in some consistent ways from those who did not, and the patterns were largely consistent with those found in studies of transfers in the absence of incentives. Applicants were more likely to be African American, unmarried, have lower salaries, and be less satisfied with their current schools' policies. Focusing on the subset of seven districts for which we had the more detailed data, we found teachers with more disadvantaged students and those at the top end of the value-added distribution more likely to apply.

Policymakers could be concerned that programs like TTI do not move teachers from the truly best schools to the truly worst schools in the district, but rather shuffle them around among middle-ranked schools to either side of the arbitrary cutoff that a program like this requires. This

is a concern for both sending and receiving schools: schools right above the cutoff might be hard to staff and still very much in need of effective teachers, whereas those right below the cut-off might not be the schools policymakers want to target with expensive incentive programs. We found real differences between the students taught by teachers before and after the transfers, but it is worth noting that students taught by transfer teachers before the program were not the district's top performers. The average test scores of these students were below their district averages in both math and reading. Although we did not study the impact of TTI on sending schools, this may be a concern for policymakers seeking to avoid moving their best teachers away from students who need them.

This study has also shed light on what happens within low-achieving schools when programs like TTI move high-performing teachers into them. Overall, we found largely positive effects and no evidence that collegiality or collaboration among teachers were undermined. Some evidence indicated principals responded strategically by reallocating teachers across grades, pairing weaker teachers with the stronger transfer teachers. We also found that transfer teachers believed that they were assigned more challenging students than their peers, but this was not supported by principal reports about student assignment or administrative data. Another potentially positive outcome was an increase in mentoring resources available for nontransfer teachers in TTI schools, as transfer teachers both used fewer mentoring resources and provided more mentoring to the others.

The first implication of the study for policymakers is that selective transfer incentives are feasible, but perhaps only on a small scale. For every vacancy targeted for intervention in a hard-to-staff school, at least 20 candidates would have to be identified and recruited—possibly more

at the middle school level. Even a large district could run out of candidates fairly quickly with large-scale implementation. For example, a goal of using transfers to fill 20 vacancies could require 400 candidates, who would represent the top 20 percent of a pool of 2,000 eligible teachers with at least three years of continuous service in tested grades in the targeted grade span and subject. Furthermore, scaling up requires more teachers to come from sending schools, raising the possibility that any given sending school will suffer a critical mass of departures.

The second implication is the suggestion that the behavioral response within a school of a selective transfer incentive program, though mostly confined to the students of the transferring teachers, may spill over into other teaching teams. In other words, attracting one or two strong teachers may not be enough to transform the whole school, but could nevertheless shift resources in ways that affect students beyond those in the transfer teachers' classrooms.

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APPENDIX A: FOCAL TEACHERS

Several analyses in this paper are based on the sample of "focal teachers," those who filled the study vacancies on treatment and control teams. Due to data limitations, identifying the focal teachers was not always possible. We knew who they were for almost all treatment teams: either the vacant position was filled by a TTI transfer teacher, or we had information about the non-TTI teacher who filled the position through the program implementation process. For control teams, however, principals were not required to communicate with us, and the identities of teachers who filled control vacancies were not tracked at the time the positions were filled. We used teacher background survey responses regarding teaching assignment and also contacted principals (separately from the principal survey) to identify teachers who were new to their teams. In several situations, however, we were not able to identify the focal teacher because information was unavailable (due to survey nonresponse from teachers or no response from the principal), a source provided information that did not agree with other sources, or information from a source contradicted other information we had about the team (e.g., more teachers reported on the survey that they were new to the team than there were known vacancies, or the principal reported there were no vacancies).

To deal with the unidentified focal teachers in our analysis, we used both selective and inclusive definitions of focal teacher status. The selective definition classified only teachers who could be linked to study vacancies based on program implementation information, principal reports, or teachers' self-reports. In the small number of cases in which these sources identified more teachers as new to the team than there had been vacancies, we designated all new teachers as focal teachers and assigned each an equal weight that summed to the number of vacancies on the team. If insufficient information was available, no focal teacher was identified for that team, and the team was not included in the selective focal teacher analysis.

For the inclusive definition, we classified at least one teacher on every team as the focal teacher, even if evidence indicating the person was the true focal teacher was limited. In cases where we could not determine which teacher was the focal teacher, we included all possible focal teachers (in some cases, all teachers on the team) and assigned each a proportional weight that summed to the number of vacancies on the team.

APPENDIX B: DATA SOURCES

The candidate survey frame consisted of all teachers identified as eligible candidates for TTI. Eligibility was determined by the value-added analysis conducted as part of program implementation. Teachers were surveyed about their teaching experience, experience with TTI and future plans, education and teaching certification, compensation, family and housing commitments, and other background information.

The teacher background survey frame included all teachers on study teams. They were identified after collecting teacher rosters from schools with study teams in the fall of the first year of the program, when TTI teachers had transferred schools. Using the rosters, we identified teachers assigned to teach study grades and/or subjects. The survey collected information about teacher experience and job satisfaction, mentoring, career transitions, teacher education and teaching certification, compensation, family and housing commitments, and background characteristics.

The principal survey frame included all principals of schools with study teams. The questionnaire collected information about recruiting, interviewing, hiring, and performance of recently hired teachers in study grades, as well as school climate and teacher relationships. Principals completed a separate survey for each team in their schools.

Table B.1 lists the survey administration method, sample sizes, and response rates for each survey.

[TABLE B.1]

Administrative data collected from each study district included student test score, demographic, and enrollment records. The students' records were linked to the teachers who taught them in math and reading. They covered the 2009–10 school year, and we received them from each district in the fall of 2010. As part of program implementation, we collected similar data for school years preceding the study from seven of the ten districts to enable us to conduct the value-added analysis to identify eligible candidates (the other three districts supplied results from value-added analyses conducted by other organizations). Finally, teacher rosters were collected from schools with study teams, as previously mentioned.

Further details regarding the experimental design and data sources are available in Glazerman et al. 2012. The survey instruments are available at http://edicsweb.ed.gov/browse/downldatt.cfm?pkg_serial_num=4024. Restricted-use files of the study data can be requested from the National Center for Education Statistics. The restricted-use files are accompanied by full documentation of data.

Table 1. Team-Level Mean Student Characteristics, by Treatment Status

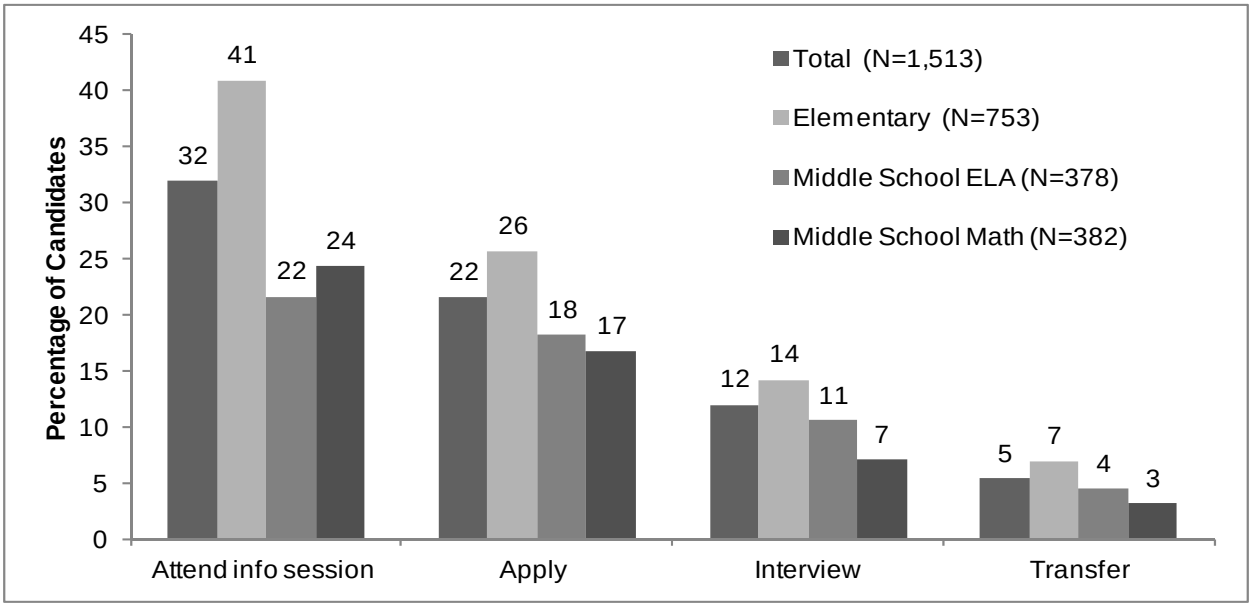
Student Characteristic	Treatment Mean	Control Mean	Difference	*p*-Value
Math Sample				
Prior achievement[a]				
Math pretest score	-0.40	-0.42	0.03	0.315
Reading pretest score	-0.51	-0.50	-0.02	0.601
Demographics (percentages)				
Male	49.6	50.9	-1.2*	0.029
Race/ethnicity				
White	5.3	4.5	0.9	0.114
African American	27.8	43.8	-16.0***	0.000
English language learner	30.5	23.7	6.8***	0.000
Special education	7.0	7.5	-0.5	0.278
FRL	83.9	80.1	3.8***	0.003
Reading Sample				
Prior achievement[a]				
Math pretest score	-0.36	-0.46	0.10**	0.024
Reading pretest score	-0.44	-0.50	0.06	0.150
Demographics (percentages)				
Male	50.7	51.1	-0.04	0.578
Race/ethnicity				
White	6.6	6.5	0.01	0.938
African American	34.8	38.8	-4.0*	0.083
English language learner	24.6	23.7	0.9	0.593
Special education	6.5	6.8	-0.3	0.438
FRL	81.1	80.4	0.7	0.476
Sample size (students) (math)	9,669	7,383		
Sample size (students) (reading)	8,420	7,489		

Source: Administrative data.

[a]Test scores are reported in standard deviations relative to the state average.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Figure 1. Take-Up Rates Among Transfer Candidates



Source: TTI program records.

Note: Transfer candidates are the teachers we identified as highest performing in their pools and within their districts who were also teaching in potential sending schools. We considered three pools: elementary, middle school English/language arts (ELA), and middle school math.

Table 2. Hiring Rates in the Treatment and Control Teacher Teams

Measure	Treatment	Control	Difference	*p*-Value
Applicants considered per vacancy	4.16	4.59	-0.43	0.658
Applicants considered per vacancy (including teams where no applicant was considered)	3.20	3.30	-0.10	0.900
Applicants interviewed per vacancy	3.10	3.22	-0.12	0.761
Applicants interviewed per vacancy (including teams where no applicant was interviewed)	2.39	2.31	0.08	0.834
Offers made per applicant interviewed	0.42	0.33	0.08	0.126
Offers accepted per offer made	0.93	0.94	-0.01	0.831

Source: Mathematica Principal Survey.

Notes: Analysis conducted at the teacher-team level. Sample sizes are 59 treatment teams and 41 control teams.

Table 3. Descriptive Characteristics of Candidates, by Application Status (percentages unless otherwise noted)

Characteristic	Did Not Apply	Applied But Did Not Transfer	Transferred	All Candidates
Demographic				
Age (in years)	46.3	43.1	42.0	45.4
Male	17.8	19.3	17.7	18.0
Black	12.5	22.1	27.2	15.0
Hispanic	15.0	13.0	14.8	14.7
Married	71.3	60.1	61.7	68.6
Have Co-Residing Children	41.8	44.4	54.3	43.1
Residential				
Own Home	87.5	79.8	81.5	85.7
Average Commute Time (in minutes)[a]	19.8	19.6	21.6	19.9
Professional				
Base Salary (dollars)	51,856	47,699	46,604	50,740
Other Compensation (dollars)	3,825	3,551	3,565	3,757
Experience in Teaching (in years)	16.9	12.7	12.5	15.9
Competitiveness of Undergraduate Institution				
Very competitive	19.3	18.4	14.8	18.9
Competitive	35.7	43.3	49.4	37.6
Has a Master's or Doctorate Degree	45.2	51.4	45.7	46.4
Has National Board Certification	11.7	7.5	11.1	11.1
In top 10% of Value-Added Ranking[b,c]	48.4	48.9	44.8	48.3
Free or Reduced-Price Lunch Students (FRL) in Sending Schools[b]	52.1	67.3	67.5	55.1
Sample Size	920	223	81	1224

Source: Mathematica Candidate Survey.

[a]Average commute time is for school year 2008–09 for candidates in cohort 1 districts and 2009–10 for candidates in cohort 2 districts.

[b]Student-level data to estimate value added was available for seven districts. Sample sizes for these variables are as follows: 728= did not apply; 133= applied but did not transfer; 46= transferred; and 907=total.

[c]Numbers in each cell refer to the percentage of candidates who were in the top 10% of value-added rankings among those in the category corresponding to that cell. For example, 48.4% of the candidates were in the top 10% among those who did not apply.

Table 4. Determinants of Applications to TTI: Logit Results

	In All Ten Districts		In Seven Districts With Student Data[b]	
Factor[a]	Marginal Effects	Standard Error	Marginal Effects	Standard Error
Dependent variable: Probability of Applying to TTI				
Income (thousands of dollars)	-0.004***	0.002	-0.002	0.002
Demographic Variables				
Male	0.010	0.036	0.020	0.042
African American	0.119***	0.037	0.072	0.049
Hispanic	0.001	0.042	-0.097*	0.051
Married with co-residing children under 5	0.104***	0.042	0.085*	0.050
Married with co-residing children aged 5 or more	0.050	0.037	0.067	0.044
Unmarried	0.108***	0.031	0.070*	0.042
Residential Variables				
Owns home	-0.053	0.037	-0.085**	0.040
Travel time in application school year (hours)	-0.010	0.058	0.014	0.067
Professional Variables				
Attended a very competitive undergraduate institution	-0.045	0.038	-0.005	0.047
Attended a competitive undergraduate institution	-0.062*	0.032	-0.024	0.043
Has master's degree or above	0.042	0.026	0.055*	0.033
Candidate for National Board certification or certified	0.021	0.033	-0.084*	0.048
Satisfaction indicators				
Satisfied with school policy	-0.102***	0.032	-0.060	0.038
Satisfied with salary	0.031	0.028	-0.015	0.034
Satisfied with professional environment	-0.067*	0.037	-0.058	0.045
Satisfied with facilities	-0.005	0.037	-0.015	0.044
Satisfied with students	0.008	0.029	0.024	0.034
In top 10% of value-added ranking			0.050*	0.030
Percentage of FRL current students			0.004***	0.001
District fixed effects	Yes		Yes	
Sample size	1,127		672	

[a]Factors included are dummy variables unless otherwise noted. Models include district fixed effects.
[b]The seven districts are those where we estimated value added and had student-level data.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

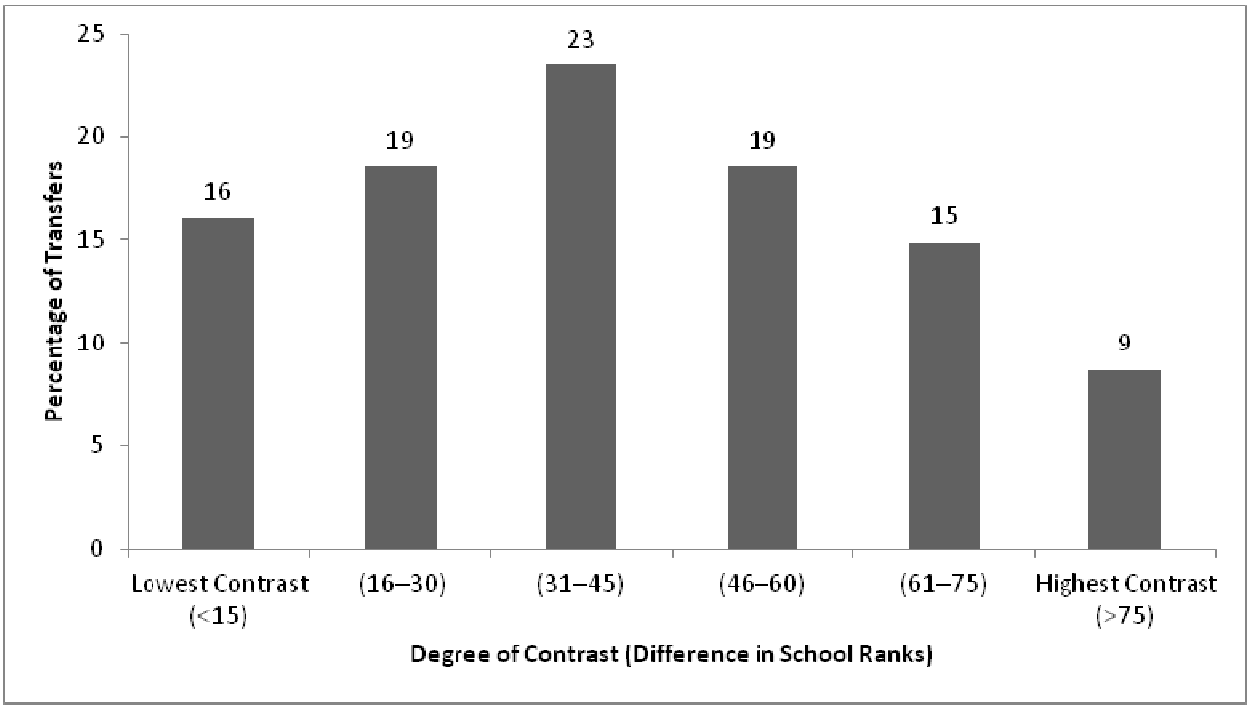
Table 5. Determinants of Transfer, Conditional on Applying: Logit Results

	In All Ten Districts		In Seven Districts With Student Data[b]	
Factor[a]	Marginal Effects	Standard Error	Marginal Effects	Standard Error
Dependent variable: Probability of Transferring to a Low-Achieving School				
Income (thousands of dollars)	-0.001	0.003	-0.000	0.003
Demographic Variables				
Male	-0.003	0.070	0.011	0.094
African American	0.132*	0.078	0.087	0.111
Hispanic	0.134	0.083	0.150	0.104
Married with co-residing children under 5	0.164*	0.090	-0.009	0.129
Married with co-residing children aged 5 or more	0.157*	0.091	0.084	0.124
Unmarried	0.094	0.080	0.075	0.117
Residential Variables				
Owns home	0.076	0.075	0.161*	0.092
Travel time in application school year (hours)	0.114	0.117	0.080	0.167
Professional Variables				
Attended a very competitive undergraduate institution	-0.014	0.087	-0.041	0.126
Attended a competitive undergraduate institution	0.030	0.066	0.054	0.106
Has master's degree or above	-0.068	0.054	-0.045	0.078
Candidate for National Board certification or certified	-0.005	0.074	0.072	0.147
Satisfaction indicators				
Satisfied with school policy	-0.013	0.058	-0.079	0.086
Satisfied with salary	0.125**	0.057	0.130*	0.073
Satisfied with professional environment	-0.084	0.064	-0.130	0.090
Satisfied with facilities	-0.040	0.067	0.160*	0.094
Satisfied with students	0.148**	0.063	0.189*	0.093
In top 10% of value-added ranking			-0.089	0.079
Percentage of FRL current students			0.001	0.002
District fixed effects	Yes		Yes	
Sample size	281		154	

[a]Factors included are dummy variables unless otherwise noted. Models include district fixed effects.
[b]The seven districts are those where we estimated value added and had student-level data.

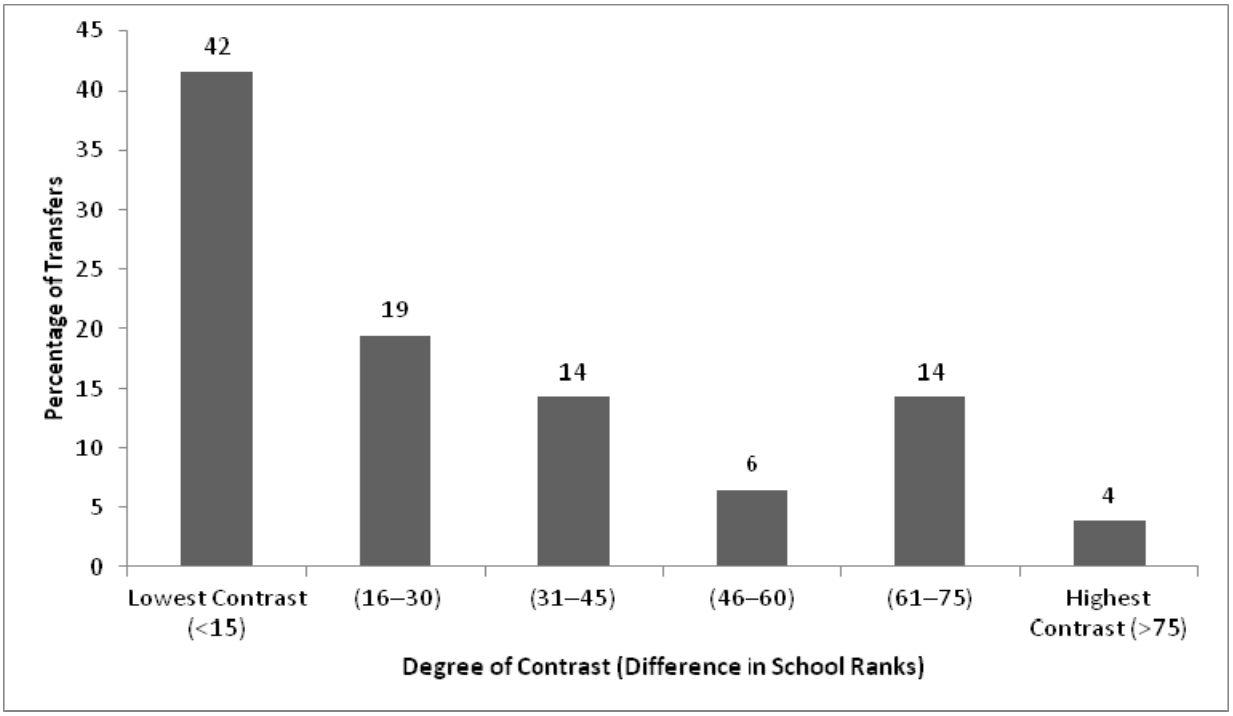
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Figure 2. Contrast Between Transfers' Sending and Receiving School by Achievement Ranks



Source: Administrative data and TTI program records (N = 81).

Figure 3. Contrast Between Transfers' Sending and Receiving School by Poverty Ranks



Source: Administrative data and TTI program records (N = 81).

Table 6. Characteristics of Selected Transfer Teachers' Students Before and After Transferring

Characteristic of Average Student (percentages unless noted)	In Sending Schools 2007–2009	In Receiving Schools 2009–2010	Difference (Receiving Minus Sending)	*p*-Value
Race/ethnicity				
White	23.7	8.7	-15.0***	0.000
African American	27.8	36.6	8.8	0.138
Hispanic	40.9	46.9	6.0	0.330
Low income (percent FRL)	68.1	92.6	24.4***	0.000
Special education[a]	10.8	11.0	0.2	0.913
Limited English proficient	15.9	15.1	-0.7	0.859
Average reading score[b]	-0.06	-0.39	-0.32***	0.001
Average math score[b]	-0.09	-0.38	-0.29***	0.000

Source: Administrative data.

Note: Data pertain to a subgroup consisting of four districts that provided student-level data. N = 52 teachers who transferred in the four districts and for whom detailed student data were available. Because of missing data, the sample size was 38 teachers for SPED and 45teachers for FRL and LEP, 43 for reading scores, and 43 for math scores. Not all teachers taught both math and reading.

[a]The special education category in two of the four districts includes gifted students.
[b]Average reading and math scores are given in fraction of a standard deviation computed within district and grade.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 7. Characteristics of Teachers Who Filled Treatment and Control Vacancies (percentages)

Characteristic	Treatment Focal	Control Focal	Difference
Professional background			
Years of experience in teaching (average years)	11.8	8.2	3.6***
Has a master's degree or doctorate	46.2	36.1	10.1
Has National Board certification	20.2	9.0	11.2**
Transferred via TTI	75.5	0.0	75.5***
Personal background			
Race/ethnicity			
White, non-Hispanic	49.5	42.1	7.4
African American, non-Hispanic	27.7	33.0	-5.3
Hispanic or Latino	16.6	15.5	1.1
Age (years)	41.8	36.5	5.3***
Married or living with a partner	62.1	54.4	7.7
Home owner	77.4	48.0	29.3***
Sample size (number of teachers)[a]	**89**	**99**	

Source: Mathematica Teacher Background Survey.

Note: Consistent with the study design, we compare all focal teachers in the treatment group to all focal teachers in the control group, regardless of how the positions were filled.

[a]The focal teacher sample is based on the selective definition of focal teachers, as described in Appendix A. The treatment group has 63 teachers instead of the 70 assigned because three transfer teachers changed grades, one vacancy was lost, and three teachers were nonrespondents. The smaller sample of control focal teachers resulted from a combination of survey nonresponse, indeterminate focal teacher status, or a combination of both.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8. Team-Level Differences between Focal Teachers' and Non-Focal Teachers' Students

Type of Difference	Percentage of Treatment Teams	Percentage of Control Teams	Difference
Difference in prior math scores			
Less than -0.25 (focal teachers assigned lower-scoring students)	28.4	25.5	2.9
-0.25 to -0.10	19.4	21.6	-2.2
-0.10 to 0.10	11.9	19.6	-7.7
0.10 to 0.25	14.9	13.7	1.2
More than 0.25 (focal teachers assigned higher-scoring students)	25.4	19.6	5.8
Difference in prior reading scores			
Less than -0.25 (focal teachers assigned lower-scoring students)	25.4	23.5	1.8
-0.25 to -0.10	19.4	21.6	-2.2
-0.10 to 0.10	19.4	25.5	-6.1
0.10 to 0.25	13.4	7.8	5.6
More than 0.25 (focal teachers assigned higher-scoring students)	22.4	21.6	0.8
Difference in percent low-income (FRL)			
More than 10% (focal teachers assigned more low-income students)	18.2	14.6	3.5
10% to 5%	7.3	7.3	0.0
5% to -5%	54.5	61.0	-6.4
-5% to -10%	10.9	14.6	-3.7
Less than -10% (focal teachers assigned fewer low-income students)	9.1	2.4	6.7

Source: Administrative data.

Note: N = 67 teams in the treatment group and 51 teams in the control group. FRL data available for selected districts, N = 55 treatment teams and 41 control teams. None of the relationships between treatment status and assigned-student difference is significantly significant based on Pearson's chi-square tests of independence.

Table 9. Characteristics of Nonfocal Stayers and Movers

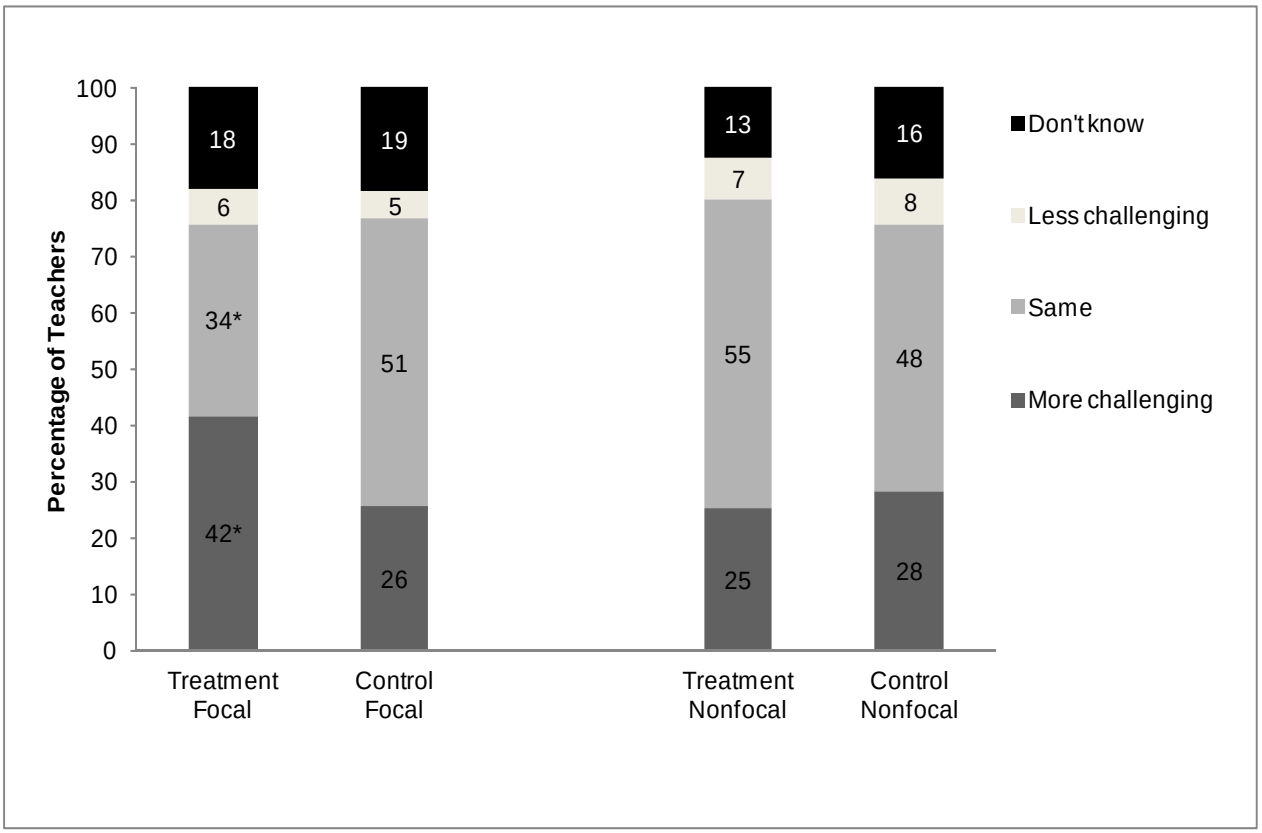
Characteristic	Treatment Mean	Control Mean	Difference	*p*-Value	Sample Size (Teachers)	
					Treatment	Control
Years of classroom experience						
All teachers	10.5	11.5	-1.0	0.292	198	176
Stayers	11.6	11.3	0.3	0.782	124	129
Movers	10.8	15.4	-4.6**	0.044	51	33
Years of teaching experience in the district						
All teachers	8.6	9.6	-1.0	0.234	198	176
Stayers	9.7	9.4	0.3	0.748	124	129
Movers	8.5	13.1	-4.6**	0.033	51	33
National Board certified (percentage)						
All teachers	13.4	17.5	-4.1	0.296	192	168
Stayers	18.5	18.8	-0.3	0.961	118	123
Movers	6.3	20.1	-13.8*	0.077	51	31

Source: Mathematica Teacher Background Survey.

Note: "Stayers" refers to teachers who were in the same school and taught the same grade/subject in the previous year. "Movers" are teachers who were in the same school the previous year but who taught a different grade or subject. We also examined differences in the selectivity of undergraduate institution, but the results were not robust to different sample definitions.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Figure 4. Classroom Assignment of Students Who Are More or Less Academically Challenging, Teachers' Perceptions, by Their Treatment and Focal Status

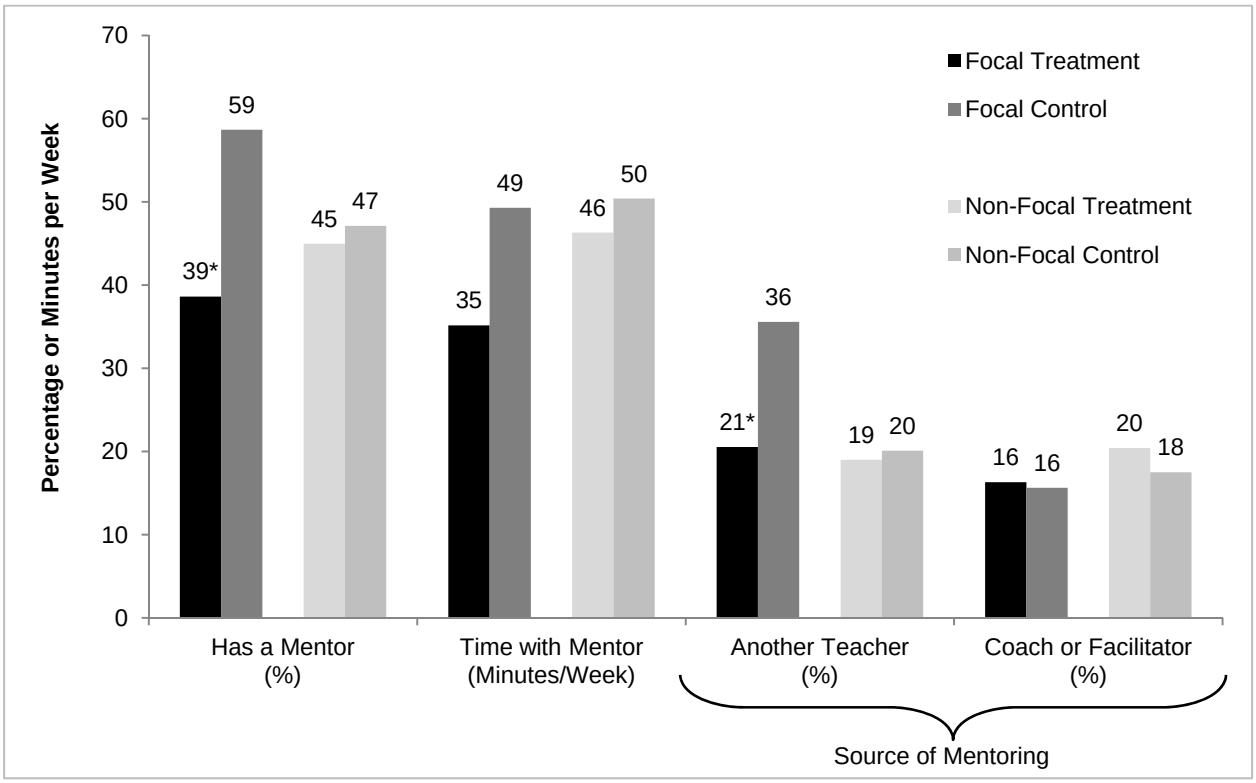


Source: Mathematica Teacher Background Survey.

Note: N = 86 treatment focal, 97 control focal, 194 treatment nonfocal, and 172 control nonfocal respondents.

*Treatment-control differences are statistically significant at the 5 percent level.

Figure 5. Mentoring Support, by Treatment and Focal Status



Source: Mathematica Teacher Background Survey.

Note: The focal teacher sample is based on the selective definition of focal teachers, as described in Appendix A. N = 87 treatment focal, 99 control focal, 199 treatment nonfocal, and 175 control nonfocal teachers.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table B.1. Survey Administration Method, Sample Sizes, and Response Rates

Survey	Administration Method	Sample Size	Response Rate		
			Treatment	Control	Total
Candidate survey	Mail with phone follow-up	1,514	n.a.	n.a.	81%
Background survey	Mail with phone follow-up	689	76%	77%	77%
Principal survey	Web with phone follow-up	165 teams	92%	88%	90%

Note: Principals were asked to complete a separate survey for each study team in their schools.
n.a. = not applicable.

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