**Teacher Applicant Hiring and Teacher Performance:
Evidence from DC Public Schools**

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Abstract

Selecting more effective teachers among job applicants during the hiring process could be a highly cost-effective means of improving educational quality, but there is little research that links information gathered during the hiring process to subsequent teacher performance. We study the relationship among applicant characteristics, hiring outcomes, and teacher performance in Washington DC Public Schools (DCPS). We take advantage of detailed data on a multi-stage application process, which includes written assessments, a personal interview, and sample lessons, as well as the annual evaluations of all DCPS teachers, based on multiple criteria. We find that several background characteristics (e.g., undergraduate GPA) as well as screening measures (e.g., applicant performance on a mock teaching lesson) strongly predict teacher effectiveness. Interestingly, we find that these measures are only weakly, if at all, associated with the likelihood of being hired, suggesting considerable scope for improving teacher quality through the hiring process.

"The best means of improving a school system is to improve its teachers. One of the most effective means of improving the teacher corps is by wise selection."

Ervin Eugene Lewis, Superintendent of Schools, Flint, Michigan, 1925

Improving selection at the hiring stage holds great potential for improving teacher quality and raising educational achievement. This notion is quite old, as evidenced by the above quotation, and continues to be motivated by findings from recent research. Teachers vary substantially in their impacts on student outcomes in both the short and long run (Chetty et al. 2014a,b) and, given this variation in teacher performance, some have argued that the greatest hiring cost faced by schools is the risk of exposing a group of students to a new teacher who turns out to be highly ineffective (Staiger and Rockoff, 2010). In addition, collection of on-the-job performance data on teachers (e.g. standardized student testing, collection of observation data, portfolios of student work) requires significant public resources and often entails difficult labor negotiations (Baker and Santora 2013) while schools and school districts have wide freedom to require teaching applicants to submit information as part of the hiring process.

Nevertheless, despite many decades of research, little progress has been made in establishing rigorous methods to select individuals likely to become successful teachers. Selection based solely on basic credentials such as certification and graduate education résumés is likely to yield few benefits. Economists, though latecomers to the issue of teacher quality, have repeatedly found that these credentials have little or no power to explain variation in performance across teachers. More recent research has shown some promising results regarding the predictive power of indices of teacher characteristics, although these have included measures collected in low-stakes research surveys (Rockoff et al. 2011) or administrative data unavailable to schools and school districts (Boyd et al. 2008). Only one concurrent study (Goldhaber et al.

2014) examines the extent to which teacher performance can be predicted using data collected as part of an actual hiring process.[1]

In this paper, we use three years of data on teacher applications, hiring, and performance in the Washington DC Public Schools (hereafter DCPS) to gain insights into how various measures might be used to improve teacher hiring. The DCPS setting presents several advantages for this purpose. First, the district implements a centralized multi-stage application process. This provides us with a number of applicant characteristics as well as evaluations on written assessments, personal interviews, and teaching auditions. Second, passing each stage of the application process was based on meeting a particular performance threshold. This allows us to separate the impact of making it through the process (and into a recommended pool of applicants) from the impact of having a high scoring application on the probability of being hired into DCPS. Third, DCPS conducts annual evaluations of all of its teachers under its "IMPACT" system, under which a wide variety of performance data is collected.[2] This allows us to evaluate the performance of teachers in all grades and subjects, as opposed to earlier work focusing on teachers whose students take standardized tests – typically math and English teachers in grades 4 – 8.

We find that several background characteristics (e.g., undergraduate GPA) as well as screening measures (e.g., applicant performance on a mock teaching lesson) strongly predict teacher effectiveness. Interestingly, we find that these measures are only weakly, if at all,

[1] Some suggestive evidence also comes from selection into two alternative certification programs in New York City. Rockoff and Speroni (2011) find that math teachers hired through the Teaching Fellows program were slightly more effective in their first year of teaching if they had a high rating during program selection. Dobbie (2011) finds that an index of eight criteria used to select applicants into the Teach for America (TFA) program are positively related to effectiveness among teachers during their first years of teaching.
[2] Dee and Wyckoff (2013) describe IMPACT's incentives in greater detail and demonstrate that the program affected teacher turnover and measured performance on various IMPACT components.

associated with the likelihood of being hired, suggesting considerable scope for improving teacher quality through the hiring process.

The rest of the paper proceeds as follows. Section 2 describes the teacher application, hiring, and evaluation processes in DCPS. In Sections 3 and 4, we present empirical findings with regard to selection into DCPS and performance among those selected. Section 5 concludes.

2. Teacher Application, Hiring, and Performance Evaluation in DCPS

In this study, we analyze data from Teach DC, a multi-stage teacher application process used in DCPS since 2009. Teach DC was developed as a means to centralize and formalize the teacher application process, with two goals in mind. First, DCPS wanted to increase its understanding of how applicant characteristics related to hiring and on-the-job performance, and therefore needed to collect standardized data. Second, DCPS sought to streamline the hiring process by screening out undesirable applicants and providing principals with a set of "recommended" candidates on which they could focus their search efforts. Importantly, successful completion of the Teach DC application process is not required for hiring into DCPS, although, as we show below, recommended candidates are far more likely to be hired than the average applicant.

We use data from applications made in the years 2011 through 2013, when the district made several notable changes to expand and improve the program. We analyze subsequent hiring and performance data from the school years 2011-12 through 2013-14. Thus, we have three cohorts of candidates and new hires, and can observe retention and performance for the 2011 applicants for up to three years.

2.1 Teach DC Application Process and Data Collection

Teacher candidates submitted their application to the Teach DC system online during the spring and summer. The initial application collected some basic background information such as education history, employment experience, and eligibility for licensure.[3] Following collection of this preliminary information, district officials reviewed applications in several stages. At the end of each stage, only applicants who pass a specified performance threshold were allowed to proceed. Applicants who pass all stages (as well as a background check) are included in the recommended pool seen online by principals.

In 2011, there were four stages of evaluation; two written evaluations (general essays and subject-specific assessments), an interview, and a teaching audition. In 2012 and 2013, the general essay was dropped, and applicants were assessed on the remaining three stages. Below we briefly summarize the key aspects of the evaluation process. Appendix A provides a more detailed explanation of the process each year. Appendix Table 1 summarizes the content of the stages in each year.

During 2011, applicants first submitted online essays of 200-400 words: one essay on instructional strategies for low-performing students, and one essay on the use of student achievement data. These essays were scored by one of several district office reviewers for content and writing quality on a 4 point scale (in 0.1 point increments), and a composite score was calculated using weights of 40% for the content of each essay and 20% for overall writing quality. As a general rule, applicants proceeded if they achieved a composite score of 2.0 or higher.

[3] Applicants deemed ineligible for a teaching license in DC are not allowed to proceed further, and we do not analyze these ineligible applications. To be licensed in DC, teachers must have a bachelor's degree, complete a teacher preparation program (traditional or alternative), and pass both the PRAXIS I and relevant PRAXIS II exams (or substitute exams). Teachers licensed in another state are also generally eligible for a DC license.

In addition to the essays used for selection at this stage, applicants were asked additional questions that were not used in the selection process and were not provided to principals that hired new teachers. Importantly, applicants were not told that these items were different than the essays or any other information that they submitted, so these data are likely indicative of responses that DCPS would receive if they were to be used in the selection process.

Applicants answered multiple-choice questions to measure the "Big Five" personality traits (Costa and McCrae, 1992) and Grit, defined as "the tendency to sustain interest in and effort toward very long-term goals." [4] In addition, applicants answered 50 multiple-choice questions from the Haberman Star Teacher Pre-Screener (Haberman, 1993), a commercial teacher applicant screening instrument. Used by a number of large urban school districts throughout the U.S., the Haberman Pre-Screener is intended to provide school officials with guidance on how effective a particular candidate is likely to be in an urban classroom.[5]

In the subject-specific written assessment, applicants were assessed on their content area knowledge and knowledge of instructional practices. Applicants selected a subject area (e.g., art, math, Biology, etc.) and level (i.e., elementary, middle, or high school) to which they were applying, and then were asked to complete a subject- and level-specific task. Most applicants were asked to read a case-study in which students demonstrate some misunderstanding about the subject and to write a 300-400 word essay explaining the nature of the students' misconceptions

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[4] Personality traits were measured using a shortened version of the Big Five Inventory (John, Donahue, and Kentle 1991) in which applicants expressed their degree of agreement with how a phrase (e.g., "I am talkative") described themselves. The 16 items focused mostly on extroversion (5 questions) and conscientiousness (5 questions), two traits linked to job performance in earlier studies (Barrick and Mount, 1991; Rockoff et al., 2011), and less on measuring agreeableness (2 questions), neuroticism (2 questions), or openness to new experience (2 questions). Grit was measured using an eight item version of the instrument developed by Duckworth and Quinn (2009). Example items include "is not discouraged by setbacks" and "has difficulty maintaining focus on projects that take more than a few months". The definition of Grit is provided at: https://sites.sas.upenn.edu/duckworth , accessed on March 17, 2014.

[5] This assessment was developed by first interviewing teachers thought to be highly effective and designing questions to capture their attitudes and beliefs. The Haberman Foundation also produces an interview protocol and scoring rubric which is intended to assist district officials in identifying individuals likely to be effective urban school teachers, although this protocol was not used in DCPS during the period of our study.

and describing instructional strategies for resolving them. In 2011 and 2012, applicants for elementary school teaching positions were required to write an essay assessing content knowledge in English language arts and to complete the Knowledge of Mathematics for Teaching (KMT) test, a multiple choice test intended to measure understanding and skills distinctly valuable to teaching math (Hill et al. 2004). Applicants for middle school math positions in these two years completed the KMT but did not have to complete an additional essay. In 2013, DCPS did not administer the KMT assessment, instead relying on essays alone to evaluate each candidate's content knowledge.

The content and writing quality of these essays were scored by a team of about six DCPS personnel in each year. Each essay was scored by one person on three dimensions, each with a 4-point-scale rubric. KMT test scores were also scaled to have a maximum of 4 points possible. Essay scores and, when applicable, KMT scores were averaged to obtain a final score to determine whether the applicant passed to the next stage. The passing threshold varied somewhat across years and was altered within the year at certain points and for certain subject areas in order to obtain enough qualified applicants.

The next stage in the application process consisted of a 30 minute interview and 10 minute demonstration lesson. Interviews were conducted by the same DCPS personnel who scored the subject-specific essays, as well as several "Teacher Selection Ambassadors" (TSAs), DCPS teachers rated Highly Effective or Effective who received training by DCPS staff in order to assist with the Teach DC selection process. Interviews could be done in person or over the phone, and applicants were asked to respond to a series of structured questions covering five areas: track record of success, response to challenges, contribution to work environment, ownership of high expectations, and continuous learning.[6] Applicants' responses were scored on a 4-point scale using a detailed rubric.

The demonstration or "mini" lesson could be done in person or submitted by video. Applicants were allowed to choose the topic for this self-contained 10 minute lesson and had the option to provide lesson materials. DCPS officials scored applicant performance according to selected dimensions of the Teaching and Learning Framework (TLF), the same rubric used to measure classroom performance under the DCPS IMPACT teacher evaluation system, which we describe in more detail below.[7] Applicant performance on the mini-lesson and interview were combined to yield a final score, and applicants scoring above a specified threshold were invited to proceed to stage 4 (see Appendix A for details of the scoring and cutoffs). In 2013, the DCPS did not require the mini-lesson and applicants proceeded to stage 4 on the basis of the interview score alone. The final stage in the Teach DC process consisted of a teaching audition in which the applicant taught a complete lesson of approximately 30 minutes. All auditions in 2011 were conducted in DCPS classrooms but were videotaped for evaluation. In 2012, applicants were permitted to submit a videotaped teaching lesson in lieu of the "live" audition, while in 2013 auditions were based completely on video submissions. In each year, DCPS staff and TSAs evaluated the auditions using the same DCPS classroom observation protocol (i.e., the TLF

[6] For example, under "response to challenges," interviewees were asked, "tell me about the most significant behavior challenge that you've encountered with a student (or group)," with follow-up questions like "what did you do first to address the challenge," "what was the result," and "what ultimately happened."

[7] Applicants receive a score of 1-4 in five areas: lead well-organized objective-driven lessons, explain content clearly, engage students in learning at all levels, check for student understanding, and maximize instructional time. The scoring rubric is quite detailed and the current version can be found at: http://dcps.dc.gov/DCPS/Files/downloads/ABOUT%20DCPS/2013-2014%20TLF.pdf. To provide an example of how scores are anchored, some of the language describing a "4" in "maximize instructional time" includes "routines, procedures, and transitions are orderly, efficient, and systematic with minimal prompting from the teacher." By contrast, a score of "1" is described by "routines or procedures are not evident or generally ineffective; the teacher heavily directs activities and transitions."

rubric mentioned above), with each audition rated by one TSA.[8] Applicants received scores from 1-4 on several different elements, with all element scores combined to yield a final score.

Table 1 shows the number of applicants evaluated in each recruiting year and each stage, as well as whether or not they passed the stage and the fraction of applicants hired in each possible stage outcome. There were roughly 2,500 applicants per year and 12-13 percent were hired into DCPS. In each year, roughly 60-70% of applicants completed the subject-specific written assessment and 30-40% of applicants completed the interview. However, the number of applicants completing the audition rose significantly after 2011, in part due to the relative ease of evaluating applicants' submissions of video instead of arranging live auditions in DCPS classrooms. Applicants did not have to make it into the Teach DC recommended pool in order to be hired into DCPS, and, in panel B, we see that in both 2011 and 2012, the percentage of applicants hired among those not even evaluated in the initial stage was only slightly below average. However, among applicants who are evaluated in each stage, those who failed the evaluation are less likely to be hired than those who passed. Among those applicants who passed the final audition stage, the fraction hired was 46 percent, 39 percent, and 54 percent in years 2011, 2012, and 2013, respectively.

Our main analyses focus on applicants' background characteristics and three composite measures drawn from the application stages: (i) a pedagogical and content knowledge (PCK) score, (ii) interview score, and (iii) audition score. Each of the three is a rescaled composite of the scores collected by DCPS. To obtain the PCK score we first standardize (mean zero, standard deviation one within years) the subject-specific essay scores on content and writing quality, as

[8] In 2013, approximately 15% of interviews and 30% of the auditions were checked by a DCPS staff member as part of a "random audit" to assess the reliability of TSA ratings. The correlation between the average scores initially assigned and those after review was 0.87 for interviews, although 45% had at least one component score changed and 17% had the final recommendation overturned. Only 20% of reviewed auditions had any component score changed, leading to roughly 10% of reviewed auditions having the final recommendation overturned.

well as the KMT score. Our “PCK score” is the average of all standardized scores available for a teacher. For 2011 and 2012 applicants, our “interview score” is the average of two component scores, each standardized: (a) the mean of the applicant’s TLF scores for the mini-lesson, and (b) the mean of the applicant’s behavioral interview questions scores. For 2013 applicants, we do not have separate scores for the mini-lesson and interview questions, but we have scores on several components (e.g., “instructional expertise,” “communication skills”) as well as several binary judgments (i.e., “outstanding,” “no reservations,” “reservations”) which we combine using factor analysis to create the 2013 interview score. For each of the three years, a factor analysis on the components of the audition score yields just one factor, and we use the factor analysis weights in each year to construct our audition score.[9]

2.2 Hiring Process

As in many large school districts, hiring in DCPS has always been (and continues to be) a largely decentralized process, done by individual schools, with school principals making final hiring decisions. To assist principals in hiring, DCPS provides an online database which lists all license-eligible applicants who have passed all stages in the Teach DC process.[10] These recommended applicants can be filtered by subject area to help principals find candidates, and principals can navigate through the online database to find out further information on how the applicants scored in the Teach DC process. While we know that DCPS principals were made aware of the online applicant database during a regularly occurring and mandatory meeting of

[9] We get virtually identical results if we use a simple unweighted average of the component scores within the audition measure.
[10] In addition to Teach DC, there are also two alternative certification programs, Teach for America and the DC Teaching Fellows, which help recruit new DCPS teachers. In the school year 2011-12, we observe over 300 new DCPS teachers in the Teach DC applicant data, while the DC Teaching Fellows program and Teach for America brought in, respectively, roughly 100 and 60 new DCPS teachers.

school administrators, the district does not track whether principals used the database, nor whether they proceeded beyond the list of candidates to view applicants' scores in any of the hiring stages. As we show below, evidence suggests that principals made use of the list of recommended candidates, but did not rely on the detailed application scores to select applicants.[11]

2.3 Performance Evaluation Process and Scores

Every summer, each DCPS teacher's performance evaluation for the previous school year is summarized in a single "IMPACT" score. This high-stakes score directly determines personnel decisions ranging from termination to significant salary increases. An IMPACT score is composed of several performance measures, which vary depending on the grade(s) and subject(s) the teacher is assigned. We observe final IMPACT scores and all component scores (described below) for all district teachers in the years 2011-12 through 2013-14.

The first component of the IMPACT score is based on measures of student learning. For teachers of math or reading in grades 4 through 8, this component includes an "individual value-added score" (IVA) based on the DC Comprehensive Assessment System (DC-CAS) standardized tests. These teachers, known as "Group 1", represent about 15 percent of DCPS teachers. All teachers are evaluated with a "Teacher-assessed Student-learning" score (TAS). At the start of the school year each teacher sets student learning goals based on non-DC-CAS assessments which are scored by the teacher, as well as weights if multiple assessments are used. The principal must approve the assessments, weights, and learning goals. At the end of the year,

[11] In personal correspondence, DCPS officials indicated their belief that few principals accessed information beyond examining teachers in the recommended pool for the subject in which they were interested in hiring. Also, it is important to note that the online database includes neither the personality measures nor the Haberman teacher screener score collected in 2011.

the principal validates the assessment scores and evaluates accomplishment of the learning goals using a rubric.[12] Additionally, in 2011-12 (and earlier years), 5 percent of all teachers' final IMPACT score is a measure of school value-added on DC-CAS tests.

The second component of all teachers' evaluation is a classroom observation score. Each teacher is typically observed five times during the year, three times by a school principal and twice by a "master educator" (i.e., an experienced teacher whose conducts observations full-time at many schools). Teachers' performance during classroom observations is scored using the district's own Teaching and Learning Framework (TLF) rubric.[13] Observers assign scores of 1-4 in several areas of practice which are averaged within observations, and then these composites are averaged across observations.[14]

The remaining two evaluation components are assessed solely by the school principal. Principals rate each teacher's "commitment to the school community" (CSC) using a rubric that covers partnerships with parents, collaboration with colleagues, and support for school-wide initiatives and high expectations. Last, the school principal can deduct a certain number of points from a teacher's final IMPACT score on the basis of poor attendance, tardiness, disrespect of others, or failure to follow policies and procedures. This last component is known as "core professionalism" (CP).

Teachers' final IMPACT scores are a weighted average of the various component scores; Appendix Table 1 summarizes the weights, which changed between the school years 2011-12 and 2012-13. The final IMPACT score determines the teacher's impact rating category, based

[12] In the 2011-12 school year (and before) IVA was the only student learning component for Group 1 teachers even though these teachers do have TAS scores.

[13] The TLF rubric is modified somewhat for teachers in kindergarten and younger classrooms, and teachers who work with special education or English language learner students in non-traditional settings. A separate rubric is used for teachers working with students with autism.

[14] Examples of areas of practice include "explains content clearly", "engages students at all learning levels", "provides students multiple ways to move toward mastery", "checks for student understanding", "maximizes instructional time and builds a supportive", and "learning-focused classroom."

on pre-specified ranges. There are four possible ratings: ineffective, minimally effective, effective, and highly effective.

Teachers in the ineffective category are immediately dismissed. Teachers are also dismissed if they fall in the minimally effective category for two consecutive years. At the other end of the distribution, teachers scoring in the highly effective category receive a one-time bonus of as much as $25,000. If a teacher is rated "highly effective" for two consecutive years, she received a substantial permanent increase in salary; Dee and Wyckoff (2013) estimate this could be worth a 29 percent increase in current value of total earnings over a 15 year horizon.

Our primary measure of job performance combines the several IMPACT component scores using weights determined by factor analysis. Specifically, we first conduct a factor analysis of the scores: overall classroom observation, the individual value-added (if available), the teacher-assessed student achievement (if available), commitment to school community, and core professionalism. In every year, this analysis yields only one significant "performance factor," which we standardize (mean zero, standard deviation one) within school years. Using a standardized version of the official, district-generated IMPACT score teachers actually received yields similar results. We prefer the performance factor because the data indicate very similar weights on each component across years, while there were considerable changes across years in weights used by IMPACT (e.g., the TAS component score is completely omitted from the calculation of IMPACT for Group 1 teachers in 2011).

2.4 Sample & Descriptive Statistics

We use data on 7,640 individuals who applied through Teach DC in the three years 2011-2013 and were eligible for a teaching license in DC.[15] Table 2 presents summary statistics for applicants' SAT scores, undergraduate GPA and college selectivity (using a six category ranking developed Barron's Profiles of American Colleges (2009)), teaching experience, and other background measures. Note that we do not have data on the applicant's race or gender; the district is not permitted to require that applicants provide this information.

Table 3 shows the pairwise correlations among several key background characteristics and application performance scores. While every correlation is positive, they are all fairly low in magnitude and some are not statistically significant. The highest correlations are between the interview and audition scores, which are roughly 0.2. The PCK score is not significantly correlated with either the interview or audition measures.[16] These correlations suggest the potential for each stage in the application process to be capturing distinct information about teaching applicants, rather than repeatedly measuring the same characteristics and skills. Of course, low correlations also may indicate a considerable amount of noise in each score. The three measures of a candidate's academic achievement (SAT score, undergraduate GPA, and selectivity of undergraduate institution) are all modestly positively correlated, and are slightly negatively correlated with a candidate's prior experience in teaching. There are small positive correlations between these academic achievement measures and application performance scores.

The bottom panel of Table 3 presents a correlation matrix for the 2011 application cohort that includes the additional measures collected in that year. In general, these additional measures

[15] We drop 198 applicants who participated in a Fast Track application option in 2011. Our results are not sensitive to including these applicants.

[16] The magnitudes of the correlations vary somewhat across cohort, although the general pattern of strong vs. weak associations are similar.

are not at all highly correlated with any of the other application performance measures. Exceptions include a modest correlation between extraversion and interview score (0.15) and between the Haberman score and the PCK score (0.21).

3. Association between Applicant Characteristics and Likelihood of Being Hired

To examine the relationship between applicant characteristics and the likelihood of being hired, we estimate a series of linear probability models of the form:

$$(1.1) \quad H_i = \beta \boldsymbol{X_i} + \Sigma_s \delta^s D^s{}_i + \varepsilon_i$$

where H_i is an indicator for hire into DCPS, $\boldsymbol{X_i}$ is a vector of teacher characteristics, and $D^s{}_i$ is an indicator for the highest stage the individual reached in the Teach DC application. The coefficients of interest are contained in the vector β—to what extent do applicant characteristics predict hire into DCPS, controlling for whether the applicant was listed in the recommended pool of candidates (which we know strongly predicts hiring).

For ease of exposition, we present results separately for applicant background variables (e.g., prior teaching experience, SAT/ACT score) and scores on the TeachDC assessments (e.g., interview). These variables are almost completely uncorrelated (as seen in Table 3), and including controls for TeachDC assessment scores has no impact on the coefficients for applicant background characteristics, or vice versa. Because the availability of teaching positions and the supply of candidates may vary widely by subject area and over time, we present results that include fixed effects for the subject area and grade level for which the applicant applied, interacted with the application year. Not all candidates have complete data for all characteristics, and we set missing values to zero and include a set of missing variable indicator flags into the regression. We base our statistical inferences off of heteroskedasticity-robust standard errors.

Table 4 presents the results from regressions in which teacher background characteristics are entered separately and then simultaneously. It is particularly interesting to compare the results in column 3 and 4. The specification in column 4 includes controls for the highest stage in the TeachDC process that applicants reached. For this reason, significant coefficients on these background characteristics in column 4 reflect the importance that school principals place on these characteristics or other unmeasured factors correlated with these factors. Several interesting patterns emerge. Regardless of whether we control for the highest application stage reached, applicants with some prior teaching experience are more likely to be hired than individuals with no prior experience. For example, the coefficients on 3-5 and 6-10 prior years of experience in column 4 indicate that these teachers are respectively 2.2 and 4 percentage points more likely to be hired than their peers. In column 3, we see that applicants who attended more selective undergraduate institutions are significantly more likely to be hired than those from non-selective institutions. However, in column 4 we see that the influence of college selectivity operates entirely by helping applicants proceed further through the TeachDC process.

Interestingly, neither undergraduate GPA nor SAT score is significantly associated with hiring (columns 1 and 3). However, applicants with higher GPA and SAT scores made it further through the TeachDC process, so that conditional on the stage reached these factors are negatively associated with the likelihood of being hired (columns 2 and 4).

Table 5 presents estimates from equation (1.1) that includes applicant background characteristics as well as application scores. The coefficients on applicant background characteristics are not shown, but are virtually identical to those presented in the analogous specification in Table 4. Each of the three application scores is positively associated with the likelihood of being hired when they are entered separately (column 1). A one standard deviation increase in the PCK written test is associated with a 5.5 percentage point increase in the likelihood of being hired, which is quite large given the baseline rate of roughly 12 percent. Interview and audition scores show an even stronger association. For example, a one standard deviation increase in the audition score, conditional on the written test and interview scores along with the background characteristics, is associated with a 12.7 percentage point increase in the change of being hired. When all three scores are included simultaneously, the coefficients on the PCK written test and the interview drop substantially but the coefficient on the audition score remains virtually unchanged (column 3).

Importantly, in column 4 when we include fixed effects indicating the highest stage reached by the applicant, the coefficients on the three application score measures drop by over 75 percent. Indeed, the PCK written test is no longer a significant predictor. This suggests that principals did not rely heavily on the information collected in the application process beyond the recommendation and that the factors that the principals did rely on were not highly correlated with these scores (conditional on the other factors).

Table 6 presents regression results for 2011 alone that focus on the relationship between the personality measures and Haberman index and hiring. Extraversion and the Haberman Index are both positively associated with the likelihood of being hired, even after controlling for the other personality measures and background characteristics. Importantly, the Haberman index is not significantly related to hiring once we condition on the highest stage reached. This will make us more confident in interpreting the coefficient on the Haberman Index in performance regressions.

4. Association between Applicant Characteristics and Effectiveness as a Teacher

Table 7 presents summary statistics on through groups of DCPS teachers: (i) teachers hired through the TeachDC process between 2011 and 2013, which will serve as our primary analytic sample; (ii) teachers hired between 2011 and 2013 outside of the TeachDC process; and (iii) teachers hired before 2011. New hires are substantially less likely to be African-American than existing teachers, and are more likely to be teaching in middle school. Looking at the bottom of the table, we see new hires have substantially lower IMPACT scores than existing teachers, which is not surprising given the well-established correlation between experience and effectiveness.

To examine the relationship between applicant characteristics and teaching effectiveness, we estimate a series of regression models of the form:

(1.2) $$performance_{it} = \beta + X_i + S_i + \sum_s \delta^s D_i^s + SbjYr_{it} + \varepsilon_{it}$$

where i indexes individual teachers and t indexes the academic year. Note that we observe each newly hired teacher between one and three times, so our sample is an unbalanced panel. In this model, *SbjYr* is a series of fixed effects for the subject and grade level the individual is teaching interacted with the academic year, and the other variables are the same as described in equation (1.1). For variables with missing values, we set missing to zero and include a missing variable indicator flag into the regression. We show heteroskedasticity-robust standard errors that are clustered by teacher.[17]

Table 8 presents OLS estimates from equation (1.1). Columns 1 and 2 show results when variables are entered separately; columns 3 and 4 show results when teacher characteristics are entered simultaneously. In column 4 we see that a teacher's undergraduate GPA and college selectivity are positively related with performance. For example, the coefficient Barron's rank

[17] We have also estimated models that cluster by school and by teacher and school, and obtain virtual identical results.

suggests that a teacher who attended a college one unit higher on this selectivity scale (e.g., moving from competitive to very competitive) receives a performance rating .11 standard deviations higher. This is notable because in the results in Table 4 indicate that conditional on the other variables in the model, teachers are not hired on the basis of college selectivity.

Table 9 shows the relationship between the application scores and teacher performance. Columns 1-2 show the application scores entered one at a time; columns 3-4 show analogous estimates but this time with all of the applications entered simultaneously. We see that each of the applications have a modest positive association with the teacher effectiveness measure. In column 4, which controls for the highest-stage reached by applicants, we see that the PCK written test and the interview are large and significant predictors of teacher performance. Recall from Table 5 that the PCK measure was not at all related to hiring and the other two measures were only weakly related to hiring. A one standard deviation increase in either the PCK written test or the interview is associated with a teaching performance score roughly 0.25 standard deviations higher. The coefficient on the audition sore is very imprecise, but the point estimate is also positive. As a robustness check, Table 10 presents similar estimates for a variety of alternative teaching performance measures. The results all mimic those presented in Table 9.

Table 11shows results from the performance regressions limited to the 2011 hire cohort, focusing on the unique teacher characteristics measured in this year. The most interesting result to emerge is that the Haberman Index is significantly associated with teacher performance. Specifically, a one standard deviation increase in an applicant's score on the Haberman Index is associated with a .20 standard deviation increase in measured effectiveness, even after controlling for the other background characteristics and the highest stage reached in the application process.

In order to assess how well these factors predict teacher effectiveness, we calculate the predicted performance for each applicant based on a least squares regression where the dependent variable is job performance measured by the first predicted factor from a factor analysis of IMPACT evaluation component scores, standardized. The covariates include all of the "background characteristics" covariates in table 8 and the "score" covariates in table 9. The specification also includes highest-stage-reached by year fixed effects, subject-taught by year fixed effects, and indicators for second year in the district and third year in the district. We do so using a leave-one-out procedure so that the outcome for an individual teacher does not influence his or her own predicted score.[18] Figure 1 plots kernel densities estimated separately by quartile of predicted performance using teacher-by-year observations. It appears that teachers in the top quartile of predicted effectiveness score roughly 1 standard deviation higher in actual effectiveness than their peer applicants who scored in the bottom quartile. This illustrates that the predictions captured by the application measures incorporate considerable information regarding actual effectiveness.

5. Conclusions

We study the relationship among applicant characteristics, hiring outcomes, and teacher performance in Washington DC Public Schools (DCPS). We find that several background characteristics (e.g., undergraduate GPA) as well as screening measures (e.g., applicant performance on a mock teaching lesson) strongly predict teacher effectiveness. Interestingly, we find that these measures are only weakly, if at all, associated with the likelihood of being hired, suggesting considerable scope for improving teacher quality through the hiring process.

[18] Specifically, to obtain the predicted value for teacher i, we estimate our model using all observations except for those from teacher i. Using the coefficients from this regression and teacher i's Xs, we calculate the predicted value for teacher i.

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Table 1--Applicant progress through TeachDC process

		2011 applicants			2012 applicants			2013 applicants		
(A) Cumulative Progression in TeachDC		#	%	Fraction hired	#	%	Fraction hired	#	%	Fraction hired
Started TeachDC and Eligible to Teach:		2,360	100%	0.14	2,527	100%	0.12	2,555	100%	0.12
General	Completed Stage:	2,186	93%	0.14						
Essay	Passed Stage:	1,958	83%	0.15						
Content	Completed Stage:	1,596	68%	0.16	1,740	69%	0.13	1,514	59%	0.19
Knowledge	Passed Stage:	1,066	45%	0.22	1,118	44%	0.18	1,254	49%	0.23
Interview +	Completed Stage:	752	32%	0.27	814	32%	0.22	1,104	43%	0.25
Sample Lesson	Passed Stage:	513	22%	0.35	531	21%	0.31	920	36%	0.30
Teaching	Completed Stage:	244	10%	0.40	492	19%	0.32	618	24%	0.40
Audition	Recommended Pool:	164	7%	0.46	392	16%	0.40	462	18%	0.52
(B) Stage reached in TeachDC process		#	%	Fraction hired	#	%	Fraction hired	#	%	Fraction hired
Eligible but Initial Stage Incomplete:		174	7%	0.13	787	31%	0.10	1,041	41%	0.02
General	Failed this Stage:	228	10%	0.03						
Essay	Incomplete Next Stage:	362	15%	0.08						
Content	Failed this Stage:	530	22%	0.06	622	25%	0.04	260	10%	0.02
Knowledge	Incomplete Next Stage:	314	13%	0.09	304	12%	0.09	150	6%	0.05
Interview +	Failed this Stage:	239	10%	0.09	283	11%	0.05	184	7%	0.03
Sample Lesson	Incomplete Next Stage:	269	11%	0.32	39	2%	0.18	302	12%	0.08
Teaching	Failed this Stage:	80	3%	0.28	100	4%	0.01	156	6%	0.04
Audition	Recommended Pool:	164	7%	0.46	392	16%	0.40	462	18%	0.52

Note: Authors' calculations. "Stage reached" is the highest stage in which the data include a score or pass/fail determination.

Table 2--Characteristics of applicants

	All applicants		Applicants hired	
	Obs.	Mean (st.dev.)	Obs.	Mean (st.dev.)
	(1)	(2)	(3)	(4)
Hired	7,442	0.13	934	1
Undergraduate GPA	7,112	3.40	894	3.41
		(0.43)		(0.44)
Undergraduate major	7,196		911	
Education		0.34		0.31
Liberal arts, humanities, social sciences		0.33		0.33
Professional degrees		0.10		0.11
STEM		0.08		0.09
Art		0.06		0.07
Other		0.10		0.10
Undergraduate college Barron's ranking	6,588		865	
Barron's rank (1-5)		2.83		2.89
		(1.02)		(1.09)
Barron's "special" (binary)		0.01		0.01
Not ranked by Barron's (binary)		0.12		0.10
SAT math+verbal (or ACT equiv)	4,600	1148.72	645	1146.49
		(175.15)		(169.66)
Prior teaching experience	7,314		933	
Novice		0.33		0.28
1 to 2		0.17		0.18
3 to 5		0.18		0.20
6 to 10		0.17		0.20
11 or more		0.14		0.13
Subject and grade applying to teach	6,418		881	
Eelementary or ECE		0.38		0.41
Special education		0.11		0.11
English language learners		0.03		0.03
High school or middle school…				
Math or science		0.11		0.13
Social studies		0.11		0.06
English		0.10		0.08
Foreign languages		0.03		0.04
Visual or performing arts		0.07		0.07
PE and health		0.04		0.05
Other		0.02		0.01

Note: Authors' calculations. Excluding applicants who were not eligible for a teaching license in DC.7,442 total observations.

Table 3--Pairwise correlation of applicant characteristics and scores

		SAT	GPA	Barron's	Exper.	PCK	Interv.	Aud.	Essay	Extrov.	Agree.	Cons.	Neuro.	Open.	Grit	Haberman
										Big Five Index						
2011-2013 applicants	SAT math+verbal (or ACT equiv)	1														
	Undergraduate GPA	0.32	1													
	Undergraduate Barron's ranking	0.36	0.13	1												
	Years of teaching experience	-0.06	-0.11	-0.14	1											
	PCK written test	0.21	0.15	0.19	-0.12	1										
	Interview	0.15	0.12	0.1	-0.03	0.10	1									
	Audition	0.09	0.06	0.04	0.04	0.10	0.22	1								
2011 applicants only	Teaching essay	0.19	0.15	0.23	-0.18	0.21	0.17	0.04	1							
	Big Five Index															
	Extroversion	0.07	0.02	0.03	-0.12	0.07	0.15	0.13	0.07	1						
	Agreeableness	0.06	0.03	0.05	0.05	0.06	0.08	-0.08	0.08	0.11	1					
	Conscientiousness	-0.04	0.04	-0.03	0.02	0.01	0.05	-0.03	0.02	0.24	0.31	1				
	Neuroticism	0.00	0.06	0.06	-0.04	0.03	-0.01	-0.03	-0.01	-0.25	-0.28	-0.46	1			
	Openness to experience	-0.04	-0.01	-0.02	0.02	0.00	0.06	0.01	0.05	0.26	0.25	0.34	-0.27	1		
	Grit index	-0.06	0.00	-0.03	0.05	-0.05	0.02	-0.04	0.02	0.23	0.33	0.67	-0.43	0.3	1	
	Haberman total score	0.21	0.20	0.21	-0.14	0.21	0.11	0.01	0.26	0.13	0.16	0.08	-0.05	0.12	0.06	1

Note: Pairwise correlations of applicant characteristics and scores. Maximum observations for a cell 7,442, see Table 1.

Table 4--Applicant background characteristics and hiring

	Characteristics separately		Characteristics simultaneously	
	(1)	(2)	(3)	(4)
Years prior experience, novice omitted				
1 to 2	0.025*	0.017	0.027*	0.018+
	(0.012)	(0.010)	(0.012)	(0.010)
3 to 5	0.025*	0.021*	0.030**	0.022*
	(0.011)	(0.010)	(0.011)	(0.010)
6 to 10	0.037**	0.041**	0.048**	0.040**
	(0.012)	(0.010)	(0.012)	(0.011)
11 or more	0.004	0.024*	0.021+	0.025*
	(0.012)	(0.011)	(0.013)	(0.012)
Undergrad GPA (std)	0.005	-0.016**	0.004	-0.012**
	(0.004)	(0.004)	(0.004)	(0.004)
SAT math+verbal (std)	-0.001	-0.019**	-0.005	-0.015**
	(0.005)	(0.005)	(0.005)	(0.005)
Barron's rank (1-5)	0.009*	-0.004	0.008*	-0.000
	(0.004)	(0.003)	(0.004)	(0.004)
Barron's "special" (binary)	-0.026	-0.024	-0.021	-0.026
	(0.038)	(0.034)	(0.038)	(0.034)
Not ranked by Barron's (binary)	-0.026*	-0.008	-0.021+	-0.011
	(0.012)	(0.011)	(0.013)	(0.011)
Highest-stage-reached by year fixed effects		√		√
Adjusted R-squared			0.024	0.206

Note: Estimates from an LPM with 7,442 observations where being hired is the dependent variable. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-4 each report estimates from a single regression. Each specification includes year-by-subject-applied fixed effects. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate.

+ indicates p < 0.10, * 0.05, and ** 0.01

Table 5--Application scores and hiring

	Scores separately		Scores simultaneously	
	(1)	(2)	(3)	(4)
PCK written test (std)	0.054**	0.002	0.009+	0.001
	(0.005)	(0.006)	(0.005)	(0.006)
Interview (std)	0.097**	0.022**	0.053**	0.020**
	(0.006)	(0.008)	(0.006)	(0.008)
Audition (std)	0.147**	0.037**	0.138**	0.032*
	(0.009)	(0.013)	(0.009)	(0.013)
Highest-stage-reached by year fixed effects		√		√
Adjusted R-squared			0.162	0.205

Note: Estimates from an LPM with 7,442 observations where being hired is the dependent variable. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-4 each report estimates from a single regression. Each specification includes year-by-subject-applied fixed effects. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate.

+ indicates p < 0.10, * 0.05, and ** 0.01

Table 6--Additional 2011 applicant background characteristics and hiring

	Characteristics separately		Characteristics simultaneously		
	(1)	(2)	(3)	(4)	(5)
Positive spin factor (std)	-0.018	-0.015	-0.019+	-0.016	-0.016
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Negative spin factor (std)	0.010	0.014	0.010	0.014	0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Big Five Index: Extroversion	0.029**	0.018*	0.027**	0.017*	0.018*
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
Haberman total score	0.019**	0.006	0.017*	0.004	0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Highest-stage-reached by year fixed effects		√		√	√
Additional background characteristics controls					√
Adjusted R-squared			0.027	0.127	0.133

Note: Estimates from an LPM with 2,360 observations (all from 2011) where being hired is the dependent variable. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-5 each report estimates from a single regression. Each specification includes year-by-subject-applied fixed effects. "Additional background characteristics" are the covariates shown in Table 4. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate.

+ indicates p < 0.10, * 0.05, and ** 0.01

Table 7--DCPS teacher characteristics

	Hired before 2011 first year in data		New hires, first year on the job: Non TeachDC		New hires, first year on the job: TeachDC	
	Obs.	Mean (st.dev.)	Obs.	Mean (st.dev.)	Obs.	Mean (st.dev.)
	(1)	(2)	(3)	(4)	(5)	(6)
Female	2920	0.76	842	0.75	927	0.75
Race/ethnicity	2704		380		823	
Black		0.60		0.39		0.44
White		0.32		0.42		0.47
Hispanic		0.04		0.11		0.05
Asian		0.04		0.08		0.01
Other		0.01		0.00		0.03
Age	2914	42.32	820	29.97	900	31.41
School type	2917		839		926	
Education center		0.17		0.19		0.18
Elementary school		0.46		0.38		0.44
Middle school		0.09		0.17		0.15
High school		0.25		0.23		0.20
Other		0.03		0.03		0.03
Performance						
Overall performance factor score (std)	2817	0.09	806	-0.58	903	-0.39
		(0.98)		(1.03)		(1.03)
Final IMPACT score	2920	315.04	842	290.50	930	297.93
		(45.36)		(48.51)		(46.88)
Minimally effective or lower	2920	0.09	842	0.18	930	0.14
Highly effective or effective	2920	0.24	842	0.08	930	0.12
Math value-added	253	0.04	87	-0.24	101	-0.15
		(0.98)		(1.11)		(0.98)
Reading value-added	268	0.03	89	-0.15	130	-0.08
		(1.00)		(0.98)		(0.98)

Note: Authors' calculations. Sample restricted to DCPS teachers with IMPACT scores. Calculations based on one observation per teacher, the first year they appear in the data.

Table 8--Job performance and background characteristics

	Characteristics separately		Characteristics simultaneously	
	(1)	(2)	(3)	(4)
Years prior experience, novice omitted				
1 to 2	0.070	0.094	0.075	0.079
	(0.089)	(0.090)	(0.085)	(0.085)
3 to 5	0.106	0.118	0.185*	0.197*
	(0.101)	(0.097)	(0.092)	(0.089)
6 to 10	0.002	0.026	0.119	0.124
	(0.093)	(0.093)	(0.087)	(0.089)
11 or more	-0.269*	-0.206+	-0.125	-0.096
	(0.116)	(0.115)	(0.111)	(0.111)
Undergrad GPA (std)	0.259**	0.247**	0.229**	0.226**
	(0.035)	(0.037)	(0.035)	(0.037)
SAT math+verbal (std)	0.174**	0.147**	0.067+	0.049
	(0.040)	(0.040)	(0.039)	(0.038)
Barron's rank (1-5)	0.155**	0.143**	0.113**	0.112**
	(0.030)	(0.030)	(0.030)	(0.030)
Barron's "special" (binary)	0.022	0.070	0.137	0.137
	(0.234)	(0.248)	(0.225)	(0.234)
Not ranked by Barron's (binary)	0.007	0.045	0.062	0.075
	(0.107)	(0.105)	(0.105)	(0.104)
Highest-stage-reached by year fixed effects		√		√
Adjusted R-squared			0.128	0.147

Note: Estimates from least squares regressions with 1,581 teacher-by-year observations, and 917 unique teachers. The dependent variable is job performance measured by the first predicted factor from a factor analysis of IMPACT evaluation component scores, standardized. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-4 each report estimates from a single regression. Each specification includes year-by-subject-taught fixed effects, and indicators for second year in the district and third year in the district. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate. Clustered (teacher) standard errors in parentheses.
+ indicates $p < 0.10$, * 0.05, and ** 0.01

Table 9--Application scores and job performance

	Scores separately		Scores simultaneously	
	(1)	(2)	(3)	(4)
PCK written test (std)	0.264**	0.269**	0.244**	0.269**
	(0.053)	(0.056)	(0.051)	(0.055)
Interview (std)	0.295**	0.276**	0.270**	0.257**
	(0.047)	(0.054)	(0.048)	(0.054)
Audition (std)	0.163**	0.176*	0.114*	0.119+
	(0.060)	(0.072)	(0.058)	(0.070)
Highest-stage-reached by year fixed effects		√		√
Adjusted R-squared			0.120	0.132

Note: Estimates from least squares regressions with 1,581 teacher-by-year observations, and 917 unique teachers. The dependent variable is job performance measured by the first predicted factor from a factor analysis of IMPACT evaluation component scores, standardized. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-4 each report estimates from a single regression. Each specification includes year-by-subject-taught fixed effects, and indicators for second year in the district and third year in the district. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate. Clustered (teacher) standard errors in parentheses.
+ indicates p < 0.10, * 0.05, and ** 0.01

Table 10--Application scores and alternative measures of job performance

	IMPACT score	IMPACT rating: Bottom two	IMPACT rating: Top two	TLF class observation: Overall	TLF class observation: Principal	TLF class observation: Master ed	CP	CSC	TAS	Value-added: Avg.	Value-added: Math	Value-added: Read
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PCK written test (std)	0.203**	-0.031*	0.064**	0.171**	0.192**	0.099*	0.043**	0.272**	0.167**	0.054	0.258+	-0.036
	(0.055)	(0.014)	(0.017)	(0.052)	(0.053)	(0.046)	(0.015)	(0.051)	(0.048)	(0.103)	(0.143)	(0.119)
Interview (std)	0.199**	-0.061**	0.030	0.257**	0.256**	0.197**	0.033+	0.203**	0.145**	-0.043	0.116	-0.132
	(0.051)	(0.015)	(0.020)	(0.049)	(0.048)	(0.048)	(0.019)	(0.054)	(0.054)	(0.096)	(0.163)	(0.116)
Audition (std)	0.086	-0.022	0.039	0.093	0.119+	0.052	0.063**	0.148*	-0.036	-0.160	-0.283	-0.179
	(0.066)	(0.020)	(0.026)	(0.063)	(0.065)	(0.058)	(0.021)	(0.072)	(0.075)	(0.144)	(0.204)	(0.198)
Adjusted R-squared	0.140	0.070	0.067	0.142	0.105	0.155	0.022	0.104	0.048	-0.071	-0.027	-0.073
Teacher-year	1581	1581	1581	1581	1581	1574	1581	1581	1581	281	158	210
Teacher observations	917	917	917	917	917	914	917	917	917	191	108	147

Note: Estimates from least squares regressions. The dependent variables are indicated in the column headers. Each column reports estimates from a single regression. Each specification includes year-by-subject-taught fixed effects, highest-stage-reached by year fixed effects, and indicators for second year in the district and third year in the district. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate. Clustered (teacher) standard errors in parentheses.

Table 11--Additional 2011 applicant background characteristics and job performance

	Characteristics separately		Characteristics simultaneously		
	(1)	(2)	(3)	(4)	(5)
Positive spin factor (std)	0.030	0.002	0.012	-0.004	-0.023
	(0.061)	(0.060)	(0.062)	(0.060)	(0.059)
Negative spin factor (std)	-0.002	0.028	-0.036	-0.012	-0.007
	(0.073)	(0.073)	(0.073)	(0.072)	(0.074)
Big Five Index: Extroversion	-0.001	-0.008	-0.030	-0.030	-0.031
	(0.059)	(0.061)	(0.055)	(0.056)	(0.056)
Haberman total score	0.287**	0.269**	0.296**	0.276**	0.209**
	(0.054)	(0.055)	(0.054)	(0.055)	(0.055)
Highest-stage-reached by year fixed effects		√		√	√
Additional background characteristics controls					√
Adjusted R-squared			0.128	0.145	0.209

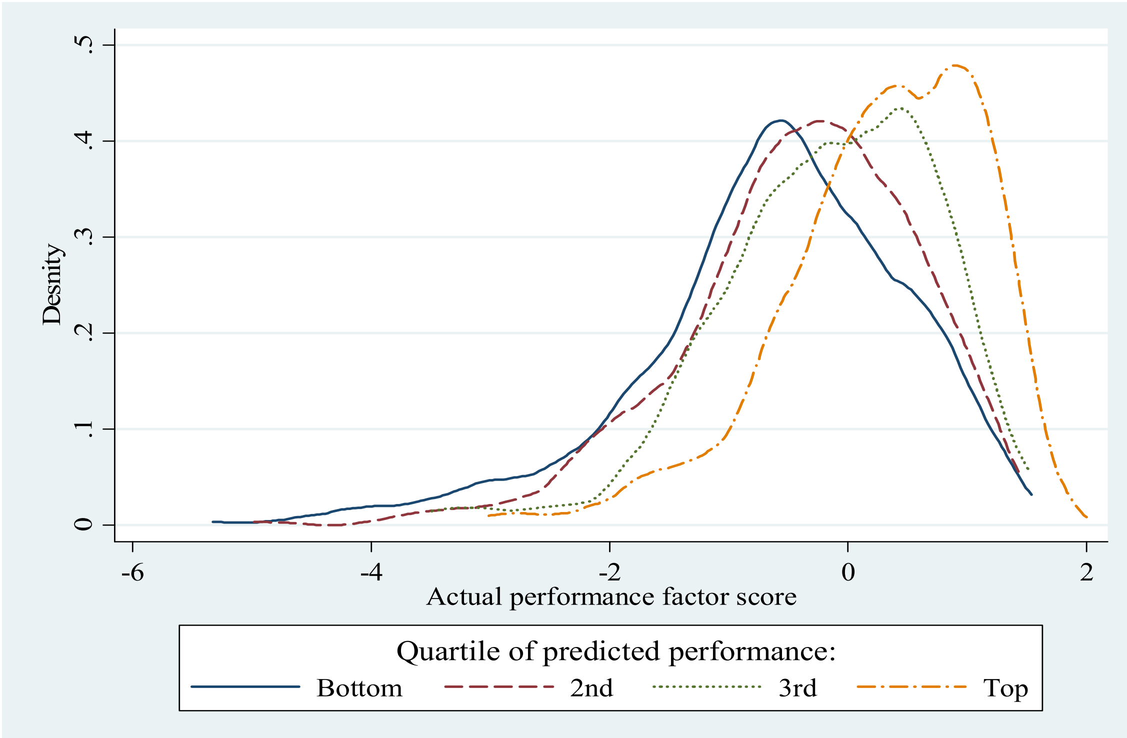
Note: Estimates from least squares regressions with 744 teacher-by-year observations, and 314 unique teachers (hired in 2011 only). The dependent variable is job performance measured by the first predicted factor from a factor analysis of IMPACT evaluation component scores, standardized. In columns 1-2 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 3-5 each report estimates from a single regression. Each specification includes year-by-subject-taught fixed effects, and indicators for second year in the district and third year in the district. "Additional background characteristics" are the covariates shown in Table 8. When a covariate is missing for an observation, we set the value to zero and include an indicator = 1 for anyone missing that covariate. Clustered (teacher) standard errors in parentheses.

+ indicates p < 0.10, * 0.05, and ** 0.01

Table 1a--IMPACT component weights

	2011-12		2012-13 and 2013-14	
	Group 1	Group 2	Group 1	Group 2
Individual value-added	0.50		0.35	
Teacher assessed student learning		0.10	0.15	0.15
Teaching and learning framework	0.35	0.75	0.40	0.75
Commitment to school community	0.10	0.10	0.10	0.10
School value-added	0.05	0.05		

Figure 1 - Relationship between screening measures and performance



Note: Kernel densities estimated separately by quartile of predicted performance using teacher-by-year observations. Predicted performance is estimated in a least squares regression where the dependent variable is job performance measured by the first predicted factor from a factor analysis of IMPACT evaluation component scores, standardized. The covariates include all of the "background characteristics" covariates in table 8 and the "score" covariates in table 9. The specification also includes highest-stage-reached by year fixed effects, subject-taught by year fixed effects, and indicators for second year in the district and third year in the district.