# 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 the 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

It has long been thought that teacher selection is an important tool for improving educational outcomes, and this notion finds much support in recent research. Teachers vary substantially in their impacts on student outcomes in both the short and long run (Chetty et al. 2014a,b, Jackson 2013, 2014), and estimates suggest there are large benefits to removing teachers who perform poorly on the job (Gordon et al. 2006, Hanushek 2011, Goldhaber and Theobald, 2013). However, policies that improve selection in hiring among existing pools of applicants may be far more *cost effective* because they avoid losses from exposing students to an ineffective teacher (Staiger and Rockoff, 2010) and would not require compensating teachers for the added risk of job separation (Rothstein, 2015).[1]

Nevertheless, establishing rigorous methods to select individuals likely to become successful teachers has proven difficult.[2] Selection using basic credentials such as certification and completion of graduate education is likely to yield few benefits. Economists, though latecomers to the issue of teacher quality, have consistently found that these credentials have little or no power to explain variation in performance across teachers (Rockoff 2004, Rivkin et al. 2005, Kane et al. 2008, Harris and Sass 2011).

In this paper, we use data on applications, employment, and teacher performance in the Washington, DC Public Schools (hereafter DCPS) to gain insights into how various measures

[1] In addition, collection of performance data on teachers (e.g. standardized student testing, classroom observation, portfolios of student work) requires significant public resources and often entails difficult labor negotiations (e.g., Baker and Santora 2013) while schools and school districts have wide freedom to require applicants to submit information as part of the hiring process.

[2] Limited progress has not been due to a lack of attention by academics. Indeed, Morsh and Wilder (1954) provide an extensive review of hundreds of studies conducted over the first half of the 20th century, beginning with Meriam (1906). We would argue that the lack of progress has been due to (a) the use of small samples, (b) the focus on a limited set of credentials, such as educational attainment, which are commonly collected in administrative data, and (c) the limited availability of high quality performance measures on teachers.

might be used to improve teacher hiring. Our data and setting present several advantages for addressing this issue. First, DCPS implements a centralized multi-stage application process that provides us with a large sample of applicants for whom we have a range of characteristics, including scores on written assessments, personal interviews, and teaching auditions. Second, passing each stage of the application process was based on meeting a particular score threshold. This helps 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. In other words, because applicants with medium scores and applicants with very high scores both earned admission to a central candidate pool, we can look for whether principals valued some characteristics over others in their hiring decisions. Third, DCPS conducts annual evaluations of all of its teachers under its "IMPACT" system, under which a wide variety of performance data is collected.[3] This allows us to evaluate teacher performance in all grades and subjects, not only on teachers whose students take standardized tests annually in math and English.

We find that several background characteristics (e.g., undergraduate GPA) as well as screening measures (e.g., applicant interview scores) 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. Only a few background characteristics, and none of the application screening measures, are significantly associated with retention.

The paper proceeds as follows. Section 2 provides an overview of current knowledge on teacher hiring practices and earlier research that informs our study. In Section 3 we describe

[3] 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.

teacher application, hiring, and evaluation processes in DCPS. We present empirical findings on selection into DCPS, job performance, and attrition in Section 4, and Section 5 concludes.

## 2. What Do We Know About Teacher Selection?

We devote this section to providing an overview of existing work, much of it from fields other than economics, on the issue of teacher selection. Economists have paid far greater attention to the labor supply of teachers than to labor demand. Many studies examine determinants of attrition and mobility between schools among employed teachers, mainly focusing on the impacts of compensation and student/school characteristics (e.g., Dolton and van der Klaauw, 1995, 1999; Hanushek et al. 2004; Scafidi et al. 2007; Clotfelter et al. 2008; Jackson 2009; Boyd et al. 2011).[4] An assumption (sometimes implicit) in much of this work is that employment outcomes stem from teachers' choices, not those of school or district administration.

Below, we restrict our attention to papers focusing more narrowly on the questions of teacher labor demand and employee selection. Other work in economics presents evidence on how teacher characteristics relate to high-stakes evaluations by principals (Jacob and Walsh 2011), and how retention decisions by school principals respond to lowering the cost of dismissal (Jacob 2013) or the provision of new teacher performance data (Rockoff et al. 2012). These papers are related to our study, but deal with on-the-job personnel assessment, rather than hiring.

[4] There are also studies focusing on how teacher effort, measured by absence, responds to incentives such as employment protection (Jacob 2013), paid absence policies (Jacobson 1989) or school accountability (Ahn 2013).

*2.1 Economics Literature*

There is a small literature in economics on the demand for teaching applicant characteristics and the effectiveness of teacher selection processes. Ballou (1996) finds that high achieving college graduates with teaching credentials are not more likely to receive a job offer, despite being no less likely to apply for teaching jobs or accept offers given to them. He concludes that "public school officials undervalue cognitive skills and subject matter knowledge when screening new applicants and that hiring decisions are suboptimal as a result." Recent work finds some supporting evidence for this conclusion. Hinrichs (2014) sent resumes with randomly generated characteristics to a representative sample of schools nationwide and measured total rates of response as well as responses with invitations for an interview. This has the distinct advantage of isolating labor demand, but is limited to basic resume credentials and to initial interest, rather than ultimate hiring decisions. He finds that applicants from more selective colleges and those from within the same state had higher rates of response, but undergraduate GPA was unrelated to response rates.

Boyd et al. (2011) use data on applications to transfer schools within New York City and the subsequent transfers that take place to discern whether transfer applicants with certain characteristics are more likely to be hired. While the use of applications data allows them to measure and control for some components of labor supply, they cannot observe declined job offers, so this aspect of labor supply could potentially affect their conclusions. Nevertheless, they find that, conditional on application, transfer applicants are more likely to be hired if they possess higher certification exam scores, attended more competitive colleges, had more years of experience, or if their previous students had higher achievement growth. This last result suggests that school principals are able to identify more effective teachers among transfer applicants.

Studying dismissals of probationary teachers in the Chicago Public Schools, Jacob (2011) finds that principals are more likely to release individuals with more absences and lower value-added scores, and less likely to release individuals with stronger educational qualifications measured by things such as the competitiveness of their undergraduate college and whether they had ever failed a teacher certification exam.

In contrast, earlier work by Kane and Staiger (2005) presents evidence from a natural experiment suggesting that schools are not effective at choosing the most effective applicants among new hires. Taking advantage of a state incentive for reduced class sizes, Los Angeles dramatically increased hiring of new elementary teachers in 1997, from around 1,300 per year to over 3,300.[5] Despite the hiring spike (and a clear increase in new hires that did not possess proper credentials), estimates of performance were no worse for teachers hired in 1997 than for cohorts hired in preceding years.

Some recent research has produced promising results regarding how indices of teacher characteristics predict teaching performance, 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).[6] Moreover, these studies focus on the characteristics of teachers who are currently hired rather than data on the characteristics of a pool of teacher applicants. This is potentially important because the absence of performance data on applicants who are not hired can create selection bias.

[5] Hiring remained high for additional years, and Los Angeles did not increase teacher salaries.
[6] Some suggestive evidence also comes from 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.

In a study which is most closely related to our work, Goldhaber et al. (2014) examine data from Spokane, Washington, where applications are scored subjectively based on information submitted on education, qualifications and certifications, experience, letters of recommendation, and narrative statements.[7] They find that teachers with higher rated applications have significantly higher impacts on student achievement (i.e., value-added) and higher retention rates, and they conclude that selection due to non-random hiring has little impact on their results.[8]

### *2.2 Hiring Preferences and Processes in Teaching*

Outside of economics, there is a significant literature on teacher hiring. These studies focus mostly on either (a) the characteristics that principals look for in job applicants and (b) the processes used by schools to recruit, screen, and select teachers. Here we give a general sense of these literatures and their findings; for more detailed reviews see Pounder (1989), Rutledge et al. (2008), or Mason and Schroeder (2010).

Studies of the values principals place on teacher applicant characteristics are based on qualitative interviews and surveys, typically with small samples drawn from either one district or a limited geographic area (e.g., Place and Kowalski 1993, Abernathy et al. 2001, Harris et al. 2007, Cannata and Engel 2011). These analyses generally indicate that principals place greater weight on personal traits (e.g., "honesty", "good character", "ability to work with peers", "respect" or "compassion" for students) that may be more difficult to assess than credentials like academic achievement or years of prior teaching experience.

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[7] Applications are scored first by central human resources staff and, if the score meets a cutoff, are scored again by school-level personnel; those with high scores in the second stage are brought in for a formal interview by the school principal and/or staff.

[8] They assess the scope of selection bias using instrumental variables methods. Applicant scores are strongly related to hiring probability in their setting, but are sometimes not calculated correctly by district staff who must add up scores on multiple criteria by hand. These arithmetic errors serve as instruments to address the selection problem.

No nationally representative study on methods used for teacher hiring exists. However, a number of studies, spanning many years and various geographic areas, provide a fairly consistent picture. The two methods employed in these studies are either to ask school district administrators about their hiring practices or to survey teachers about their experiences being hired for their most recent job (Liu and Kardos 2002, Liu and Moore-Johnson 2007).

Applicants almost always submit written applications with information including a resume and proof of certification, as well as transcripts and recommendation letters. From there, a subset of applicants is invited for in-person interview. These surveys also indicate that teachers are usually interviewed more than once as they progress toward being hired.

Submission of writing samples, a portfolio of work, or delivering a sample lesson are all far less common than the in-person interview. None of the early studies we reviewed mentioned any written evaluations other than a cover letter and they all report that a small fraction (typically less than 15 percent) of districts observed applicants teaching a lesson prior to hire.[9] More recently, Strauss (1998) reports that roughly 25% of districts surveyed in Pennsylvania solicit writing samples and roughly one third request teacher exam scores (NTE, Praxis). Balter and Duncombe (2005), surveying New York State school districts, report that 60% require a writing sample, 30% require a teaching portfolio, and two thirds require certification exam scores.[10] These surveys also report between 40 and 50 percent of districts using a sample classroom presentation, which may indicate a trend toward greater use. However, surveys of teachers (Liu and Kardos 2002, Liu and Moore-Johnson 2007) across several states typically find only about



[9] See Neely (1957), Diekrager (1969), Nalley (1971), Hansen (1976), and Luthy (1982).

[10] In addition to letters of recommendation, Pennsylvania districts reported placing high weight on college major and grade point average (but low weight on test scores, essays, or institution attended) when deciding whom to interview. In New York, recommendations and college major are also given high weight in screening prior to the interview, but low weights are given to grade point average, institution attended, and scores on certification exams (or other screening tests).

15% giving a sample lesson prior to being hired.[11] One caveat to this conclusion is that student teachers and teachers' aides who are hired to teach full-time, will likely have been observed teaching even if observation is not part of the formal hiring process.[12]

*2.3 Validity of Interviews and Job-Task Observations in Employee Selection*

A large literature in applied (or "industrial") psychology examines the power of interviews to extract reliable and accurate information about the future success of potential employees. Much of the early research in this field exposed low reliability and validity (see Schmitt 1976), but more recent work demonstrates that structured interviews (i.e., pre-selected questions with rubrics for coding answers) can predict outcome variables such as evaluations of employee performance by supervisors (see Arvey and Campion 1982, Hunter and Hunter 1984, Motowidlo et al. 1990, McDaniel et al. 1994).

A small set of studies focus on interviews for teachers specifically. However, this research typically examines how teacher characteristics (e.g., gender, age) and interview structure (e.g., a single interviewer vs. a panel) affect hiring decisions, and many of these studies use actors instead of actual teachers (e.g., Bolton 1969, Young and Pounder 1986, Young 2005). Few studies test whether interview decisions predict future success in teaching, but there is some evidence, albeit in small samples, of a positive relationship between teachers' interview ratings and supervisor ratings of job performance (Mickler and Solomon 1986) and student achievement gains (Webster 1988).

[11] The fraction of teachers who taught a sample lesson was 6.5 percent in California, 14 percent in Florida, 14.6 percent in Michigan, 19.6 percent in Massachusetts, and 23 percent in New Jersey.

[12] Liu and Moore-Johnson (2007) report that 20 percent of teachers worked in their current schools in some capacity before they were hired, and Strauss (1998) finds that about one third of school districts try to fill full-time teaching positions with current substitutes or part-time teachers.

We know of no study that focuses on the predictive validity of sample lessons done as part of a hiring process.[13] However, the power of job simulations to predict productivity is a well-researched issue in the field of industrial psychology (see Wernimont and Campbell 1968, Hunter and Hunter 1984), and there is a large literature on the relationship between student achievement and observed teacher behaviors—typically measured with trained observers using low-inference coding systems or "rubrics." This research has consistently found positive relationships between observed teacher behavior and student learning outcomes.[14] Nevertheless, while existing research supports the idea that effective teachers can be identified through observation, research settings may not accurately reflect the evaluation of sample lessons taught during the hiring process.

## 3. Application, Hiring, and Performance Evaluation in DCPS

Traditionally, hiring teachers in DCPS was a largely decentralized process, with school principals making independent decisions on whom to hire with few restrictions aside from licensing and certification. Principals could hire teachers from a variety of sources, including student teachers in their schools, through relationships with local teacher preparation programs, or through central office applications. In 2009, DCPS created TeachDC, a multi-stage, centralized application process which is the focus of our analysis and which we describe in greater detail in Section 3.1. TeachDC aims to streamline hiring by screening out less desirable applicants and giving principals a list of "recommended" candidates who successfully completed

[13] Some indirect evidence is presented by Wede (1996), who analyzed data on subjective performance evaluations of teachers from a school district that incorporated a sample lesson as part of its hiring process. Several years later, average evaluations of those hired during this period were not statistically different than those hired in prior years.
[14] Recent work includes Holtzapple (2003), Schacter and Thum (2004), Milanowski (2004), Kimball et al. (2004), Gallagher (2004), Kane et al. (2011), and Kane et al. (2012). Brophy and Good (1984) review earlier research.

the process. We examine hiring and performance outcomes for TeachDC applicants from 2011 to 2013.

Information on "recommended" TeachDC applicants is made available to principals via an online database. Recommended applicants are listed in alphabetical order, with links to their resumes, and can be filtered by subject area to help principals find candidates. Principals can also 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 are provided with information on the online database during a regularly occurring and mandatory meeting of 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 principals used the list of recommended candidates, but did not rely on the detailed application scores to select applicants.[15]

While completion of TeachDC can help applicants find a job, being on the recommended list is not required in order to be hired by a DCPS principal. Recommended candidates are quite likely to be hired (see Table 2, discussed below), but they comprise only about one quarter of new teachers hired from 2011 to 2013. An additional quarter of new hires applied to TeachDC but did not complete the process (either because they failed one of the selection stages or stopped voluntarily) and roughly one half of new hires during this time never applied to TeachDC. Of this latter group, roughly 20% arrived in DCPS through one of two alternative certification programs, Teach for America and the DC Teaching Fellows, which focus on individuals who

[15] 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.

lack teaching certification but have outstanding prior achievements and demonstrated leadership in other professions or activities.[16]

While we do not examine applicants outside of TeachDC, for comparison purposes we present summary statistics (see Table 1) on all teachers in DCPS, breaking them up by whether the teacher is a new DCPS hire who applied to TeachDC from 2011-2013 (our primary analytic sample), a new hire who did not apply to TeachDC, or a veteran teacher (hired before 2011). Relative to veteran teachers, new hires are younger, less likely to be African-American, more likely to teach in middle schools, and have lower IMPACT evaluation scores. This is true regardless of whether they applied to TeachDC. There are few noticeable differences between new hires who applied to TeachDC and those which did not, although TeachDC applicants appear to have somewhat better performance evaluations in their first year (e.g., -0.4 vs. -0.6 standard deviations on our normalized measure, the details of which are provided in section 3.2).

### *3.1 The TeachDC Application Process*

We focus on the TeachDC selection process as it occurred from 2011-2013. Each year, from roughly February through July, candidates submit applications to Teach DC. The online application system first collects background information such as applicants' education history, employment experience, and eligibility for licensure. Applicants who don't already hold a DC

[16] Over the period 2011-2013, the DC Teaching Fellows program and Teach for America brought in, respectively, roughly 100 and 60 new DCPS teachers. These teachers participate in training programs in the summer prior to starting their teaching jobs and take courses to obtain teaching certification during their first few years of employment.

license and whose credentials make them ineligible to obtain one prior to the start of the school year are not allowed to proceed further, and we do not analyze these ineligible applications.[17]

Following collection of this preliminary information, district officials review applications in several stages; we discuss these stages in detail below, as they changed somewhat from year to year. 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.

At the end of each stage, applicants who pass a specified performance threshold are allowed to proceed. Applicants who pass all stages (and a background check) are included in the recommended pool seen online by principals. On average, for those who made it through the process, it took roughly six weeks from the initial application to the pass/fail determination at the final stage.

Table 2 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, of which roughly 13 percent were hired into DCPS. 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, presumably due to the relative ease of evaluating video submissions instead of arranging live auditions in DCPS classrooms.

As mentioned above, applicants did not have to make it into the Teach DC recommended pool in order to be hired into DCPS.[18] In panel B of Table 2, we see that in both 2011 and 2012,

[17] 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.

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 and made it into the recommended pool, the fraction hired was 48 percent, 40 percent, and 52 percent in years 2011, 2012, and 2013, respectively. Thus, it seems clear that applicants who make it into the TeachDC recommended pool are far more likely to be hired, supporting the notion that principals use this list as a source for job candidates.

To give a better sense of how the TeachDC process worked in practice, we briefly summarize the key aspects of each stage during the three years on which we focus. In 2011, applicants first submitted online essays of 200-400 words which were scored by one of several district office reviewers for content and writing quality.[19] 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 explicitly 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.[20]

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[18] Table 1 shows that 28% of the 80 candidates who failed the audition stage in 2011 were nonetheless hired by the district. The analogous figures in 2012 and 2013 are notably lower. Based on conversations with DCPS officials, we believe that this is due to the fact that some of these candidates were actually moved ahead to the recommended pool to increase the choices available to principals. However, in analyses available from the authors upon request, we confirm that all of our results are robust to excluding these 80 applicants or treating them as recommended.

[19] One essay was on instructional strategies for low-performing students, and the other on the use of student achievement data. These essays were scored by 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. In addition, DCPS officials selected a random 20% subset of applicants with scores below 2.0 to pass, although applicants with the minimum possible score (1.0 on both essays) were not eligible to be selected.

[20] Prior to this entire section, applicants were informed that some of the questions were part of a pilot program, but were not told which items were part of the pilot and which were not.

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. Prior research has indicated a positive relationship between Haberman scores and teacher performance in the classroom (Rockoff et al. 2011).[21]

In addition, 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"(Duckworth and Quinn, 2009). [22] While our intention was to examine measures of the Big Five and Grit, a factor analysis (see Appendix Table A1) reveals that applicants' answers to these instruments are inconsistent with independent measurement. The only trait from these surveys that aligns well with a cohesive set of personality questions is Extroversion. All questions other than Extroversion line up along two factors corresponding to whether the question was normally scored (e.g., measuring conscientiousness, the item "Is a reliable worker") or reverse scored (e.g., measuring conscientiousness, the item "Tends to be disorganized"). We believe that this was due to the fact that the questions were asked as part of a job application rather than a low-stakes survey, and

[21] This assessment was developed by 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. The average score (out of 50) for 2011 TeachDC applicants was 34.2, with a standard deviation of 4.7, and similar to the average score of 31.9 (standard deviation 4.8) found by Rockoff et al. (2011) for a sample of recently hired NYC math teachers.

[22] Personality traits were measured using a shortened version of the Big Five Inventory (John, Donahue, and Kentle 1991) in which applicants express their degree of agreement with how a phrase (e.g., "I am talkative") describes them. 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), with less emphasis on Agreeableness (2 questions), Neuroticism (2 questions), or Openness to New Experience (2 questions). Grit was measured using a similar instrument developed by Duckworth and Quinn (2009) with eight items, such as "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.

candidates may have "faked" their responses to appear more attractive to DCPS officials.[23] Hence, in the analysis below, we include three personality measures (Extroversion, "Positive Spin", and "Negative Spin"), and the Haberman test score in regressions of DCPS hiring and teacher performance.

Applicants in all three years took a subject-specific written assessment to assess their pedagogical content knowledge (PCK) 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 a student demonstrates misunderstanding of the subject matter and to write a 300-400 word essay explaining the nature of the student's misconceptions and describing instructional strategies for resolving them. In 2011 and 2012, applicants for math teaching positions were required 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).[24] Essay content and writing quality were scored by DCPS personnel and these scores (plus the KMT test score, when applicable) were averaged to determine whether the applicant passed to the next stage. The passing threshold varied somewhat across years and was altered within the year for certain subject areas in order to obtain enough qualified applicants.

[23] A comparison with responses of roughly 400 recently hired New York City math teachers on a low-stakes survey of the Big Five (Rockoff et al. 2008, Table 2) supports this notion. NYC teachers reported levels (on a 5 point scale) of 4.11, 4.04, and 3.85 for, respectively, Agreeableness, Conscientiousness, and Openness to New Experiences. Each had a standard deviation of about 0.5. In stark contrast, the 2011 TeachDC applicants' average reported Agreeableness, Conscientiousness, and Openness to New Experiences were 4.63, 4.67, and 4.66. For other evidence on self-report bias in this context, see Mueller-Hanson et al. (2003) and Donovan et al. (2014).

[24] Elementary school applicants wrote an essay assessing content knowledge in English language arts in addition to taking the KMT test. 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.

Applicants who passed the subject-specific essay stage were invited for a 30 minute interview and to submit a 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 from DCPS staff in order to assist with the TeachDC selection process.[25]

The demonstration or "mini" lesson could be done in person or submitted by video. Applicants were allowed to choose the topic 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.[26] Applicant performance on the mini-lesson and interview were combined to yield a final score, and applicants scoring above a specified threshold, which varied somewhat across years, were invited to proceed to the final stage. In 2013, DCPS did not require the mini-lesson and applicants were evaluated on the basis of the interview alone.

The final stage in the TeachDC process consisted of a teaching audition in which the applicant taught a complete lesson of approximately 30 minutes. All auditions in 2011 were

[25] 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. 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." Applicants' responses were scored on a 4-point scale using a detailed rubric.

[26] 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."

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 rubric mentioned above), with each audition rated by one TSA.[27]



*3.2 Performance Evaluation (DCPS IMPACT)*

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.

[27] Applicants received scores from 1-4 on several different elements, with all element scores combined to yield a final score. 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.

The principal must approve the assessments, weights, and learning goals. At the end of the year, the principal validates the assessment scores and evaluates accomplishment of the learning goals using a rubric.[28] 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 who 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.[29] Observers assign scores in several areas of practice that are averaged within observations, and then these composites are averaged across observations.[30]

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 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 A2 summarizes the weights, which changed between the school years 2011-12

[28] 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.

[29] 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.

[30] 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."

and 2012-13. The final IMPACT score determines the teacher's impact rating category, based 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 receives a substantial permanent increase in salary; Dee and Wyckoff (2013) estimate this could be worth as much as a 29 percent increase in current value of total earnings over a 15 year horizon.

*3.3 Data and Descriptive Statistics*

We use data on over 7,000 individuals who applied through Teach DC in the three years 2011-2013 and who were eligible for a teaching license in DC.[31] We analyze subsequent hiring and performance data from the school years 2011-12 through 2013-14.[32] 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.

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

[32] We focus on applicants who applied for teaching jobs, and among those applicants identify new hires who are working as a DCPS teacher (as opposed to working as a counselor or administrator or any other role). We define a DCPS teacher as someone who (i) held a teaching position, as recorded in district human resources data and identified by union status, (ii) at some point during the school year. This definition includes individuals who were hired, worked in the fall, but left midyear. It also includes individuals hired midyear. Part-year teachers sometimes do not have job performance data (IMPACT scores), but we nevertheless count them as new hires. Additionally, some DCPS employees who are not officially holding a teaching position do have teaching responsibilities, and are scored in the IMPACT teacher performance evaluation program. In addition to the definition above, we count anyone with IMPACT teaching scores as a DCPS teacher. There are only two such teachers among our applicants, and the results are not sensitive to excluding them.

Two limitations in our data are worth noting. The first is that we do not possess complete information on job offers. Contrasting the outcomes "offer" and "hire" is useful for disentangling supply and demand. We have data on offers only for two of three years: 2012 and 2013. In those years roughly two-thirds of offers were accepted (68.9 percent). Additionally, based on correspondence with DCPS officials, we believe some job offers are made informally first; and, if turned down by the candidate, the offer is never recorded by the school principal in the DCPS data system. This informal first step may partly explain a very high acceptance rate, 94.8 percent, of offers made to TeachDC applicants in the "recommended" pool.

A second shortcoming is that we cannot observe teacher hiring or performance in DC charter schools. Although they enroll close to half of local students, charter schools are governed by a separate authority, the DC Public Charter School Board. We are also unable to observe if applicants take a job in another school district, such as in Virginia or Maryland.

Table 3 presents summary statistics for applicants' SAT scores, undergraduate GPA and college selectivity (using a categorical ranking developed from Barron's Profiles of American Colleges (2009)), teaching experience, and other background measures.[33] The first set of columns of Table 3 is based on all applicants, while the second is based on those who are hired.

One third of all applicants have no prior full-time teaching experience, while another third have between one and five years and the remaining third have more than five years. Among those hired, there are noticeably fewer rookie teachers (28 percent). Average self-reported undergraduate GPA (3.40) and composite SAT/ACT scores (1149) are nearly identical for all applicants, while college selectivity is slightly higher among hired applicants (2.9 vs. 2.8

[33] 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.

on a scale from 1-5).[34] A minority of applicants attended undergraduate or graduate school in Washington DC (12 percent), but they are overrepresented among those hired (17 percent). About half report having received a master's degree, in education or any field, or a higher degree.

Our analysis of application measures focuses on three composites drawn from the stages that were common for all cohorts of applicants: (i) a pedagogical content knowledge (PCK) score, (ii) an interview score, and (iii) an 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 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.[35]

Table 4 shows the pairwise correlations among applicants' background characteristics and application performance scores. Academic achievement measures such as undergraduate

[34] The SAT scores reported by our sample are somewhat higher that the national average, which would have been just above 1000 for cohorts who, like most of our sample, graduated high school in the late 1990s and early 2000s.
[35] We get virtually identical results if we use a simple unweighted average of the component scores within the audition measure.

GPA, SAT/ACT score, and college selectivity all have modest positive correlations, as one would expect. Academic achievement is slightly negatively correlated with years of teaching experience, and has small positive correlations with application scores, particularly the subject – specific written assessment.

Interestingly, while the correlations among application scores themselves are positive, they are all fairly low in magnitude, with the highest correlation between the interview and audition scores (0.22). 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 bottom section of Table 4 shows pairwise correlations for the additional measures collected for the 2011 application cohort. In general, these additional measures are not at all highly correlated with any of the other application performance measures. There is a modest correlation between extraversion and interview and audition scores (0.14 and 0.13, respectively) and the Haberman score has small positive correlations of roughly 0.2 with the academic achievement measures and the subject-specific (PCK) written assessment.



## 4. Predicting Hiring with Application Characteristics

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

$$(1.1) \quad H_i = \beta \boldsymbol{X_i} + \delta P_i + \varepsilon_i$$

where $H_{it}$ is an indicator for hire into DCPS as a teacher, $\boldsymbol{X_i}$ is a vector of teacher characteristics, and $P_i$ is an indicator for passing to the end of the Teach DC process in order to be placed in the recommended pool. We interact $P_i$ with the year of application allowing $\delta$ to differ by year.[36] The coefficients of interest are contained in the vector $\beta$—to what extent do applicant characteristics predict hire into DCPS, controlling for whether the applicant was listed in the recommended pool of candidates (which strongly predicts hiring). We present results with and without the set of indicators $P_i$ in order to examine whether the relationship between hire and a given characteristics is driven by a mechanical relationship with placement on the TeachDC list of recommended candidates.

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. We have also estimated all of the analyses using Logit models, and obtain virtually identical results.

Before presenting these results, it is important to note that DCPS principals have reasonably strong incentives to hire effective teachers. Since the school year 2012-13, principal performance in DCPS has been evaluated under the IMPACT system, parallel to the evaluation for teachers. Multiple criteria, including student test scores and rubric-based evaluations by

[36] In 2011 it appears that the recommended pool was extended to applicants passing the interview stage. In addition to the indicator for passing the final audition stage, we include an indicator for passing the interview for applicants in the 2011 cohort. Thus, the vector $P_i$ includes four mutually exclusive indicators: (i) applicants who reach the recommended pool in 2013, (ii) applicants who reach the recommended pool in 2012, (iii) applicants who pass the audition in 2011, and (iv) applicants who pass the interview but not the audition in 2011. The left out category is all other applicants.

supervisors, generate an overall performance score for each principal, and low scoring principals are dismissed while high scoring principals can receive substantial bonus payments.

Table 5 presents the results on teacher hiring. We begin by discussing the background characteristics, each is first entered separately (Columns 1 and 2) then simultaneously (Columns 3 and 4). The specifications in columns 2 and 4 include controls reaching the recommended pool. Several robust patterns emerge. Applicants with no prior teaching experience are less likely to be hired by DPCS schools than individuals with prior experience. Depending on the comparison group and specification, rookie applicants have roughly a 3-5 percentage point lower probability of being hired in DCPS. In considering the role of experience in hiring, it is important to note that principals do not bear the financial burden of paying higher salaries to teachers with more experience; DCPS schools are charged an amount per teacher equal to the average teacher salary in the district, regardless of the teacher's actual salary.

For the most part, teachers with better academic credentials appear to be no more or less likely to be hired into DCPS. Without controls for reaching the TeachDC recommended pool, the coefficients on undergraduate GPA and SAT/ACT score are both close to zero and statistically insignificant, while the coefficient on college selectivity is positive but small (about 1 percentage point for each point on the Barron's scale). However, when we control for reaching the recommended pool, the coefficient on college selectivity goes to zero, and those for undergraduate GPA and SAT/ACT score become negative and significant, though small in magnitude (about 1-1.5 percentage points). The pattern is similar for the coefficients on having a master's degree, but they are never statistically significant.

These results are consistent with two interpretations. First, school principals may not put positive weight on these basic academic achievement measures when making hiring decisions, i.e., a demand side story. The notion that principals do not place positive weight on academic credentials is consistent with prior studies (Ballou 1996, Hinrichs 2014). Second, it may be that principals do place positive weight on these characteristics, but that applicants with better academic backgrounds are less likely to accept job offers from DCPS schools. We cannot definitively separate supply and demand explanations given the limitations in our data on offers. We do, however, observe many offers that were declined (one-third of offers in 2012 and 2013 did not result in a hire) permitting a partial empirical test. In the appendix Table A7 we present results like Table 5 separately for the outcome “hired” and the outcome “offered”, restricted to 2012 and 2013 applicants. The pattern of point estimates is similar regardless of whether one uses offer or hire as the dependent variable. The similarity suggests the results in Table 5 are a demand side story, not applicants’ choices about supply.

We now shift focus to the application scores—PCK, interview, and audition—reported in Table 5. Not surprisingly, each of the three application scores is positively associated with the likelihood of being hired when we do not control for reaching the recommended pool (columns 1 and 3), with coefficients rising monotonically as we move to the later stages of the TeachDC selection process. A one standard deviation increase in applicant score is associated with increases in the likelihood of being hired of 6.0, 10.8, and 15.8 percentage points for the PCK, interview, and audition, respectively.

These effects are quite large, given the baseline hiring rate of roughly 13 percent, but is likely be driven by the effect of arriving into the recommended candidate pool. Indeed, when we include fixed effects for reaching the recommended pool (Columns 2 and 4), the coefficient on the PCK written test goes essentially to zero, while those on the interview and audition drop by about 70 percent. 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). In Appendix Table A7 we show that the coefficients on the three application scores are quite similar when the outcome is offer instead of hire, a pattern consistent with a school principal demand interpretation of the results rather than applicant supply decisions.

In Appendix Table A3, we present hiring regressions separately for four groups of subjects: Elementary and Early Childhood, Middle and High School "Core" (i.e. English, math, science, and social studies), Special Education, and Other Subjects.[37] It is perhaps notable that prior experience appears unimportant for hiring in Other Subjects, but generally we find little evidence that any particular group of subjects is driving the results seen in Table 5.

For the 2011 cohort, we can also ask whether hiring is related to our measures of applicant personality and the Haberman teacher screener score. For interpretation, it is important to note that these measures were not made available to principals, because DCPS officials were uncertain about their usefulness, but this fact was not told to applicants in order for the data collection to reflect normal conditions. Extraversion and the Haberman Index are both positively associated with the likelihood of being hired (see Table 6), although the Haberman coefficient becomes small and insignificant once we condition on being in the TeachDC recommended pool.

## 5. Predicting Performance and Attrition with Application Characteristics

We now restrict our attention to TeachDC applicants that were hired by DCPS, for whom we can observe performance and attrition. Our primary measure of job performance combines the IMPACT component scores using weights determined by factor analysis. Specifically, we

[37] Other subjects include Health and Physical Education, Music, Art, Drama, Foreign Languages, English as a Second Language, Dual Language, and Career and Technical Education.

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. This consistently yields just one significant "performance factor," which we standardize (mean zero, standard deviation one) within school years.[38]

To examine the relationship between applicant characteristics and teacher performance, we estimate a series of regressions of the form:

$$(1.2)\ E_{it} = \beta \boldsymbol{X_i} + \delta P_i + \Sigma_s \alpha^s D^s{}_{it} + \varepsilon_{it}$$

where $E_{it}$ is the performance evaluation of teacher $i$ in school year $t$. $D^s{}_{it}$ is a series of binary indicators for subject-year. 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 observe each newly hired teacher between one and three times, so our sample is an unbalanced panel; accordingly, we include fixed effects for a teacher's second and third year in DCPS and we report heteroskedasticity-robust standard errors that are clustered by teacher.[39]

Two points are worth noting before we discuss the results. First, we do not take a strong stand on whether these application measures have a causal impact on teacher performance. For example, a positive coefficient on college selectivity may simply reflect the fact that individuals with other unobservable traits that are positively associated with performance (e.g., a strong work ethic and/or perhaps a privileged family background) sort into selective colleges. Given the



[38] 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).
[39] We have estimated models that cluster by school and by teacher and school, and obtain virtual identical results.

primary purpose of the teacher selection process, we do not view this as a limitation of the analysis as it would be in the standard program evaluation context.

On the other hand, we are concerned about the possibility that selection into our sample of hired teachers could bias the estimates in equation (1.2) in a way that would confound the inferences we would like to make. For example, Table 5 indicated a positive relationship between prior experience and likelihood of being hired. When we estimate the relationship between prior experience and performance using the sample of teachers who were hired, we are concerned that inexperienced teachers who were nonetheless hired may have some unobservable characteristic that is associated with performance in the classroom. In this case, we are most concerned that this unobservable factor is positively associated with teaching ability, which would lead to a negative bias in the relationship between experience and effectiveness in equation (1.2). Given the large number of covariates included in our main specifications, however, it is difficult to definitively sign any resulting selection bias. As discussed in section 5.2, we use several strategies to address such potential selection bias.

*5.1 Main results for classroom performance*

The relationships between applicant characteristics and scores and new hire performance evaluation (shown in Table 7) are strikingly different than those discussed earlier for the outcome of being hired in DCPS (Table 5). We start with regressions where background characteristics are examined in separate regressions (Column 1). Applicants reporting no prior teaching experience were less likely to be hired, but they do not perform significantly worse than those reporting 1-10 years of experience, and they have higher performance evaluations than (the small number of) TeachDC applicants who report more than 10 years of prior experience.

Applicants who had tertiary education in Washington DC were also more likely to be hired, but do not have significantly higher performance evaluations. Meanwhile, applicants' academic achievement measures (undergraduate GPA, SAT/ACT scores, college selectivity), which did not predict hiring outcomes, are all significantly positively related to performance, with substantial effect sizes of 0.15 to 0.25 standard deviations. In contrast with prior studies, we do find that teacher's with a graduate degree have higher performance scores, at least among newly hired teachers.

We find that the three application scores (PCK written assessment, interview, and audition) are all positive predictors of teacher performance, with effect sizes of roughly 0.3 for PCK and interview and an effect size of 0.17 for the audition when each score is entered in a separate regression (Table 7, Column 1). When all three scores are included simultaneously, the coefficient on the audition becomes smaller (0.12) but it still statistically significant (Column 4).

*5.2 Accounting for selection based on hiring*

To account for potential selection bias due to hiring, we include fixed effects for being in the recommended pool (Table 7 Column 2). In Table 5 we saw that the inclusion of these controls eliminated or substantially reduced the relationship between key application measures and the likelihood of being hired. The fact that there was considerable variation in characteristics among candidates *within* the recommended and non-recommended pools, and the fact that principals did *not* appear to consider this variation in selecting teachers, ironically provides us with more convincing estimates in Table 7.

We see that the estimated coefficient on our key background and application score measures are quite robust to the inclusion of these fixed effects (Table 7 Columns 2 and 5). In particular, the PCK and interview effects decline only less than five percent, while the audition coefficient falls by just over 20 percent. Recall that inclusion of these same fixed effects almost completely attenuated the relationship between application scores and whether an application was hired by a DCPS school (Table 5). This provides greater support to the notion that these results are not driven by selection on which candidates were hired into DCPS.

As a further robustness test, we have also added school fixed effects to the performance regressions, so that identification is based purely on comparisons of applicants hired into the same DCPS school. This allows us a further test of the importance of selection bias, as it may be the case that teachers with better application scores (or academic background characteristics) are hired by schools where principals give out better evaluations. These results (see Columns 3 and 6 in Table 7) are not noticeably different than those which use both within- and between-school variation for identification.

Finally, we assess the sensitivity of our results to selection bias using more formal, parametric specifications, all of which are variants of the Heckman selection model. As Heckman and Navarro-Lozano (2004) explain, inclusion of the inverse mills ratio or a more general control function based on the predicted probability of being in the sample will control for selection bias, but only under a potentially restrictive set of functional form assumptions. In order to relax these assumptions, one needs an instrument – i.e., a variable that is associated with the likelihood of being in the sample but does not directly influence the primary outcome. To create an instrument, we takes advantage of the sharp cutoffs for passing through each stage of the TeachDC process in the same way that a regression discontinuity analysis leverages discontinuities in the likelihood of treatment associated with cutoffs in an assignment variable. Appendix Figures 1-3 show the relationship between an applicant's stage score and the likelihood of passing to the next stage in the application process for stages 2-4 respectively. Consistent with the selection process established by DCPS, we see a sharp jump in the likelihood that a candidate will move to the next stage exactly at the point their score passes the threshold. The fact that this jump is not exactly one is due to several factors, including a small number of individuals who were randomly chosen to pass in an attempt to study the validity of the threshold.

Table 8 presents the results using these additional selection corrections. The dependent variable is our standardized job performance factor from IMPACT evaluation component scores. Columns 1 and 2 simply repeat the estimates in Table 7 Columns 4 and 5 for convenient comparison. Columns 3 and 4 are estimated just as Column 1 is, except that we add a quadratic function of the predicted probability of hire. We estimate the predicted probability of hire using the specification reported in Table 5 Column 3 (all characteristic and score regressors and subject-applied by year fixed effects, but no recommended-pool by year fixed effects), but with additional instruments added as regressors.

For the estimates in Column 3, we use an extremely sparse set of instruments in the hire equation – namely, four indicator variables: (i) Applicants in any year who scored above the stage 4 cut-score designated by DCPS as the threshold for the recommended pool; (ii) Applicants in 2011 who scored above the stage 3 cut-score; we assume these applicants were also placed in the recommended pool as discussed in the text; (iii) Applicants in 2011 who scored below the stage 2 cut-score but were nevertheless randomly selected to move on to stage 3; (iv) Applicants in 2011 who applied in the first weeks of the recruitment season, all of whom were allowed to move on to stage 3 regardless of their scores in stage 2 or 1. For the most part, the results in column 3 are nearly identical to those in column 2. One exception is the audition score, where the estimate using the control function is about 30 percent lower than the specification that merely controls for recommended-pool by year fixed effects. The point estimates on the interview and PCK measures drop somewhat as well, but both remain statistically significant and substantively important.

For the estimates in Column 4, we include a much more comprehensive set of instruments that are intended to replicate the RD intuition illustrated in the figures presented above. Specifically, the added instruments include five indicator variables: (i)-(iii) Applicants in any year who scored above the cut-score in stage 2, 3, and 4 respectively. And again for 2011 (iv) applicants randomly selected to advance or (v) early applicants automatically advanced. We also allow the slope on each stage score to be different above and below the stage cut-score, and include fixed effects for the highest stage an applicant was invited to complete. All these added coefficients are allowed to vary by year. The results are virtually identical to those in column 3.

In the previous discussion of hiring we offered evidence consistent with a demand side explanation—school principals' choices—rather than a supply explanation. To continue that line of analysis here we repeat Table 8 using the outcome "offer" instead of "hire" in the first stage. Our goal is a test of whether supply-side selection explains the relationships between application data and on-the-job performance. The results, using data from 2012 and 2013, are provided in Appendix Table A8. In short, the pattern of results is again quite similar to the pattern in Table 8, consistent with a demand side story.

Together these specification tests suggest that selection bias is not an important factor in our context. For the sake of simplicity, in all remaining specifications we follow the approach taken in columns 5 and 6 of Table 7 and simply include recommended pool by year fixed effects.

*5.3 Heterogeneity and Sensitivity*

As in our analysis of hiring, we explore whether there is important heterogeneity in our performance predictions across types of schools using two sample splits: (1) elementary vs. middle and high schools and (2) below and above median student poverty. We find some evidence that prior experience and applicants' audition scores are stronger predictors of performance in middle and high schools and in higher poverty schools (Appendix Table A4), but broadly speaking our estimates are fairly stable across these two dimensions of school type.

We also examine the component parts of our overall performance measure to check if the results in Table 7 are sensitive to particular aspects of the IMPACT evaluation. In general, we find consistent effects across all of the non-IVA component measures—we examine teachers with IVA separately in order to isolate differences in outcomes from differences in sample. One notable pattern is that the effects of application scores (PCK, interview, and audition) on classroom observations are 30 to 50 percent weaker for observations made by an independent "Master Educator" than for observations made by the principal, though the former are all positive and still highly significant for the PCK and interview (Appendix Table A5). We also see that prior teaching experience appears to predict TLF observation scores, but not the other performance measures (Appendix Table A5).

When we turn to teachers with IVA estimates, our sample size falls by roughly 80 percent. These results are therefore far less precise and should be taken with a great deal of caution.  Nevertheless, some interesting patterns emerge.  First, the application scores are not significant predictors of IVA (see Appendix Table A6).   While we cannot rule out meaningful effects, the evidence on the long-term effects of high value-added teachers is strong, whereas we know little about the ultimate effects of teachers do better on the "softer" performance measures such as TLF observation scores.  Correlations for DCPS teachers between value-added and each of the other components of IMPACT are modest, about 0.15 to 0.30, but all positive and significant.  Thus, one interpretation is that the value-added measures are sufficiently noisy that we cannot detect small positive effects in our small sample, but an equally plausible interpretation is that the application measures are not good predictors of teachers' impacts on high stakes standardized tests.  We hope to address this issue in the future by incorporating data for more cohorts of applicants and years of performance.

Second, prior teaching experience, a graduate degree, and college selectivity significantly predict IVA scores (see Appendix Table A6).  These measures are also predictive of classroom observation scores for this sample.  However, since we have not assessed the robustness of these findings to correct inference for multiple hypotheses, we regard them as merely suggestive and in need of further investigation.

Finally we examine the additional measures available for the 2011 cohort: self-reported personality traits and the Haberman test score.  The most interesting result to emerge is that coefficient on the Haberman score is large, positive, and significantly associated with teacher performance (Table 9). Specifically, a one standard deviation increase in an applicant's score on the Haberman Index is associated with a 0.27 standard deviation increase in measured effectiveness, even after controlling for reaching the recommended pool.

*5.4 Results for attrition*

Hiring an effective teacher will be more beneficial when this individual stays employed in the school or district for a significant period of time. We therefore examine attrition from DCPS and from an individual school as additional outcomes of interest. Because we can only observe one year of attrition for the 2013 cohort, we focus on attrition after the first year and pool the three cohorts together. As above, we separately analyze background characteristics and application scores.

We find that self-reported prior experience and academic credentials are not significant predictors of attrition in our basic specification (Columns 1 and 3 of Table 10), while having attended undergraduate or graduate school in Washington DC is strongly negatively related to attrition.[40] Because teachers who perform poorly under the IMPACT evaluation system are forced to leave DCPS, we also estimate specifications that include indicators for the teacher's IMPACT performance level (Columns 2 and 4) so as to rule out any mechanical effects driven by correlations with performance. This change in specification slightly attenuates the effect of attending school in DC, but also raises the coefficients on academic achievement and leads them to become statistically significant in some cases. Teachers with higher application scores, in contrast, are never found to be more likely to leave after the first year. Indeed, the coefficients on PCK, interview, and audition are almost all negative.

[40] Given these results on attrition, we check the sensitivity of our performance regression results to omitting controls for teachers' second and third year in DCPS, since IMPACT evaluations do improve with experience. The coefficient for applicants from the DC area increases very slightly, by about 0.01 standard deviations, and remains statistically insignificant.

## 6. Discussion and 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.

In order to assess the combined predictive power of all of the application measures, we plot the probability of being hired against predicted performance in Figure 1. First we calculate predicted first-year performance for each applicant based on all the background characteristics and application scores. We obtain coefficients for each characteristic and score by estimating a specification identical to Table 7 Column 4 but limiting the sample to new hires in their first year at DCPS.[41] We use a leave-one-out procedure so that the outcome for an individual teacher does not influence his or her own predicted score.[42] Figure 1 plots the actual proportion hired separately for the 20 vingtiles of predicted performance.[43] We see that the probability of being hired is roughly 10 percent for applicants in the bottom third of the predicted performance distribution, and only increases slightly through the next third. It is only in the top third of the predicted performance distribution that we see a sharp increase in then proportion hired. Even among the top 5 percent of applicants in terms of predicted performance, only 30 percent ended up working in the DCPS. Assuming that this is at least partly driven by demand on the part

[41] As in Table 7 Column 4 the specification includes subject-taught by year fixed effects. We do not include any between subject or year variation in our predicted performance measure. Practically, we do not include the fixed effects coefficients in the prediction.
[42] 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*.
[43] The plot points and fitted lines in Figure 1 are net of subject-applied by year fixed effects paralleling the estimates in Table 5.

DCPS schools, this suggests considerable scope for improving teacher quality through the hiring process.

To explore the relationship between the application measures and teacher performance in the classroom, Figure 2 presents box plots of actual performance for each vingtile of predicted first-year performance. This is the same predicted performance measure in Figure 1, except Figure 2 uses only observations on new hires. As suggested by the earlier regression results, we see a positive relationship between predicted and actual performance. Interestingly, it appears that the relationship is somewhat steeper at the top and bottom of the predicted performance distribution. In order to gain a better sense of the magnitude of these performance differences, Figure 3 plots kernel densities of actual performance separately by quartile of predicted performance. Teachers in the top quartile of predicted effectiveness score roughly two-thirds of a 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.

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Table 1--DCPS teacher characteristics

| | Hired before 2011 | | New hires, first year on the job | | | |
|---|---|---|---|---|---|---|
| | First year in data | | Non TeachDC | | TeachDC | |
| | Obs. | Mean (st.dev.) | Obs. | Mean (st.dev.) | Obs. | Mean (st.dev.) |
| Female | 2,920 | 0.76 | 842 | 0.75 | 927 | 0.75 |
| Race/ethnicity | 2,704 | | 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 | 2,914 | 42.32 | 820 | 29.97 | 900 | 31.41 |
| School type | 2,917 | | 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 |
| Final IMPACT score | 2,920 | 315.04 | 842 | 290.50 | 930 | 297.95 |
| | | (45.36) | | (48.51) | | (46.87) |
| Not in DCPS next year | 2,920 | 0.19 | 842 | 0.21 | 930 | 0.22 |
| Not in same school next year | 2,920 | 0.26 | 842 | 0.29 | 930 | 0.31 |

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 2--Applicant progress through TeachDC process

| | | 2011 applicants | | 2012 applicants | | 2013 applicants | |
|---|---|---|---|---|---|---|---|
| | | # | Fraction hired | # | Fraction hired | # | Fraction hired |
| Started TeachDC and Eligible to Teach: | | 2,360 | 0.14 | 2,527 | 0.13 | 2,555 | 0.13 |
| General Essay | Completed Stage: | 2,186 | 0.14 | | | | |
| | Passed Stage: | 1,958 | 0.15 | | | | |
| Content Knowledge | Completed Stage: | 1,596 | 0.17 | 1,740 | 0.14 | 1,514 | 0.20 |
| | Passed Stage: | 1,066 | 0.22 | 1,118 | 0.19 | 1,254 | 0.23 |
| Interview + Sample Lesson | Completed Stage: | 752 | 0.28 | 814 | 0.23 | 1,104 | 0.26 |
| | Passed Stage: | 513 | 0.37 | 531 | 0.33 | 920 | 0.30 |
| Teaching Audition | Completed Stage: | 244 | 0.43 | 492 | 0.34 | 618 | 0.40 |
| | Passed Stage: | 164 | 0.48 | 392 | 0.42 | 462 | 0.52 |
| *(B) Stage reached in TeachDC process* | | # | Fraction hired | # | Fraction hired | # | Fraction hired |
| Eligible but Initial Stage Incomplete: | | 174 | 0.13 | 787 | 0.10 | 1,041 | 0.02 |
| General Essay | Failed this Stage: | 228 | 0.04 | | | | |
| | Incomplete Next Stage: | 362 | 0.09 | | | | |
| Content Knowledge | Failed this Stage: | 530 | 0.06 | 622 | 0.05 | 260 | 0.02 |
| | Incomplete Next Stage: | 314 | 0.09 | 304 | 0.09 | 150 | 0.06 |
| Interview + Sample Lesson | Failed this Stage: | 239 | 0.09 | 283 | 0.05 | 184 | 0.03 |
| | Incomplete Next Stage: | 269 | 0.32 | 39 | 0.18 | 302 | 0.09 |
| Teaching Audition | Failed this Stage: | 80 | 0.31 | 100 | 0.01 | 156 | 0.04 |
| | Passed Stage: | 164 | 0.48 | 392 | 0.42 | 462 | 0.52 |

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

Table 3--Characteristics of TeachDC applicants, 2011-2013

| | All applicants | | Applicants hired | |
|---|---|---|---|---|
| | Obs. | Mean (st.dev.) | Obs. | Mean (st.dev.) |
| Hired | 7,442 | 0.13 | 982 | 1 |
| Prior teaching experience | 7,314 | | 978 | |
| Novice | | 0.33 | | 0.28 |
| 1 to 2 | | 0.17 | | 0.19 |
| 3 to 5 | | 0.18 | | 0.20 |
| 6 to 10 | | 0.17 | | 0.20 |
| 11 or more | | 0.14 | | 0.14 |
| Undergraduate GPA | 7,112 | 3.40 | 939 | 3.42 |
| | | (0.43) | | (0.44) |
| SAT math+verbal (or ACT equiv) | 4,600 | 1148.72 | 674 | 1148.75 |
| | | (175.15) | | (168.58) |
| Undergraduate college Barron's ranking | 6,588 | 2.81 | 907 | 2.91 |
| | | (1.24) | | (1.26) |
| Master's degree or higher | 7,442 | 0.51 | 982 | 0.54 |
| Location of undergrad or grad school | 7,076 | | 940 | |
| DC | | 0.12 | | 0.17 |
| Maryland or Virginia | | 0.28 | | 0.28 |
| Outside DC, MD, VA | | 0.60 | | 0.55 |

Note: Authors' calculations. Excluding applicants who were not eligible for a teaching license in DC.7,442 total observations. Location indicators are mutually exclusive, applicants with multiple locations coded based on location nearest DC.

Table 4--Pairwise correlations of applicant characteristics and scores

| | | SAT | GPA | Barron's | Exper. | PCK | Interv. | Aud. | Essay | Personality Extrov. | Personality Pos. | Personality Neg. | Haberman |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2011-2013 applicants | SAT M+V (or ACT equiv) | 1 | | | | | | | | | | | |
| | Undergraduate GPA | 0.31 | 1 | | | | | | | | | | |
| | College Barron's ranking | 0.34 | 0.13 | 1 | | | | | | | | | |
| | Years of teaching experience | -0.05 | -0.10 | -0.14 | 1 | | | | | | | | |
| | PCK written test | 0.22 | 0.16 | 0.19 | -0.11 | 1 | | | | | | | |
| | Interview | 0.13 | 0.12 | 0.08 | -0.02 | 0.10 | 1 | | | | | | |
| | Audition | 0.08 | 0.06 | 0.03 | 0.04 | 0.10 | 0.22 | 1 | | | | | |
| 2011 applicants or | General essay | 0.19 | 0.15 | 0.23 | -0.17 | 0.19 | 0.17 | 0.04 | 1 | | | | |
| | Personality questions | | | | | | | | | | | | |
| | Extroversion | 0.07 | 0.02 | 0.06 | -0.12 | 0.06 | 0.14 | 0.13 | 0.07 | 1 | | | |
| | Positive spin | -0.04 | 0.01 | -0.01 | 0.04 | -0.02 | 0.04 | -0.01 | 0.05 | 0.28 | 1 | | |
| | Negative spin | -0.05 | 0.01 | -0.04 | 0.04 | -0.02 | 0.04 | -0.04 | 0.01 | 0.26 | 0.70 | 1 | |
| | Haberman total score | 0.21 | 0.20 | 0.19 | -0.14 | 0.20 | 0.12 | 0.01 | 0.25 | 0.13 | 0.11 | 0.07 | 1 |

Note: Pairwise correlations of applicant characteristics and scores. Maximum observations for a cell is 7,442, see Table 2.

Table 5--Hiring

| | Characteristics separately | | Characteristics simultaneously | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years prior experience | | | | |
| 1 to 2 | 0.029* | 0.023* | 0.027* | 0.025* |
| | (0.012) | (0.011) | (0.011) | (0.011) |
| 3 to 5 | 0.027* | 0.024* | 0.024* | 0.025* |
| | (0.012) | (0.011) | (0.011) | (0.011) |
| 6 to 10 | 0.040** | 0.042** | 0.041** | 0.042** |
| | (0.012) | (0.011) | (0.011) | (0.011) |
| 11 or more | 0.006 | 0.026* | 0.027* | 0.029* |
| | (0.013) | (0.012) | (0.012) | (0.012) |
| Undergrad GPA (std) | 0.006 | -0.014** | -0.010* | -0.011* |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| SAT math+verbal (std) | 0.000 | -0.016** | -0.016** | -0.015** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Barron's Rank (linear 0-5) | 0.009* | -0.002 | 0.001 | -0.000 |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| Master's degree or higher | 0.009 | -0.001 | -0.006 | -0.007 |
| | (0.008) | (0.007) | (0.008) | (0.008) |
| Location of undergrad or grad school | | | | |
| DC | 0.056** | 0.057** | 0.055** | 0.057** |
| | (0.013) | (0.012) | (0.012) | (0.012) |
| Maryland or Virginia | 0.014 | 0.026** | 0.022** | 0.025** |
| | (0.009) | (0.008) | (0.009) | (0.008) |
| PCK written test (std) | 0.060** | 0.008+ | 0.015** | 0.008 |
| | (0.005) | (0.005) | (0.006) | (0.005) |
| Interview (std) | 0.108** | 0.028** | 0.058** | 0.024** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Audition (std) | 0.158** | 0.053** | 0.148** | 0.050** |
| | (0.010) | (0.012) | (0.010) | (0.012) |
| Recommended-pool by year FE | | √ | | √ |
| Adjusted R-squared | | | 0.167 | 0.207 |
| F-statistic subject-applied by year FE | | | 1.65 | 1.26 |
| p-value | | | 0.000 | 0.052 |
| F-statistic recommended-pool by year FE | | | | 92 |
| p-value | | | | 0.000 |

Note: Estimates from linear regressions 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. Location indicators are mutually exclusive, applicants with multiple locations coded based on location nearest DC. The recommended-pool by year FE include four mutually exclusive indicators: (i) applicants who reach the recommended pool in 2013, (ii) applicants who reach the recommended pool in 2012, (iii) applicants who pass the audition in 2011, and (iv) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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 characteristics from 2011 applicants and hiring

| | Characteristics separately | | Characteristics simultaneously | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Positive spin factor (std) | -0.015 | -0.013 | -0.016 | -0.013 |
| | (0.012) | (0.011) | (0.012) | (0.011) |
| Negative spin factor (std) | 0.006 | 0.011 | 0.006 | 0.010 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Big Five Index: Extroversion (std) | 0.030** | 0.019** | 0.028** | 0.018* |
| | (0.008) | (0.007) | (0.008) | (0.007) |
| Haberman total score (std) | 0.018* | 0.005 | 0.012 | 0.002 |
| | (0.007) | (0.007) | (0.008) | (0.007) |
| General teaching essay (std) | 0.018* | 0.001 | 0.015+ | 0.001 |
| | (0.008) | (0.008) | (0.009) | (0.008) |
| Recommended-pool FE | | √ | | √ |
| Number of observations | | | 2,360 | 2,360 |
| Adjusted R-squared | | | 0.027 | 0.133 |
| F-statistic subject-applied FE | | | 1.95 | 1.12 |
| p-value | | | 0.002 | 0.300 |
| F-statistic recommended-pool FE | | | | 143 |
| p-value | | | | 0.000 |

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 3-4 each report estimates from a single regression. Each specification includes year-by-subject-applied fixed effects. The recommended-pool FE include two mutually exclusive indicators: (i) applicants who pass the audition in 2011, and (ii) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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--Job performance

| | Characteristics separately | | | Characteristics simultaneously | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Years prior experience | | | | | | |
| 1 to 2 | 0.081 | 0.100 | 0.024 | 0.100 | 0.098 | 0.058 |
| | (0.089) | (0.090) | (0.077) | (0.082) | (0.083) | (0.073) |
| 3 to 5 | 0.121 | 0.101 | 0.109 | 0.163+ | 0.156+ | 0.182* |
| | (0.101) | (0.099) | (0.083) | (0.088) | (0.088) | (0.078) |
| 6 to 10 | 0.017 | 0.034 | 0.080 | 0.069 | 0.064 | 0.115 |
| | (0.093) | (0.092) | (0.083) | (0.086) | (0.087) | (0.083) |
| 11 or more | -0.255* | -0.214+ | -0.163 | -0.104 | -0.109 | -0.054 |
| | (0.115) | (0.117) | (0.112) | (0.109) | (0.109) | (0.105) |
| Undergrad GPA (std) | 0.259** | 0.243** | 0.185** | 0.181** | 0.185** | 0.160** |
| | (0.035) | (0.037) | (0.036) | (0.034) | (0.035) | (0.035) |
| SAT math+verbal (std) | 0.173** | 0.155** | 0.092* | 0.019 | 0.019 | -0.011 |
| | (0.040) | (0.039) | (0.037) | (0.038) | (0.038) | (0.038) |
| Barron's Rank (linear 0-5) | 0.155** | 0.149** | 0.098** | 0.108** | 0.109** | 0.088** |
| | (0.029) | (0.029) | (0.027) | (0.027) | (0.027) | (0.025) |
| Master's degree or higher | 0.230** | 0.215** | 0.173** | 0.116+ | 0.112+ | 0.079 |
| | (0.065) | (0.064) | (0.056) | (0.062) | (0.062) | (0.055) |
| Location of undergrad or grad school | | | | | | |
| DC | -0.030 | 0.020 | 0.045 | -0.016 | -0.020 | 0.037 |
| | (0.096) | (0.094) | (0.079) | (0.085) | (0.087) | (0.081) |
| Maryland or Virginia | -0.131+ | -0.085 | -0.004 | -0.076 | -0.075 | -0.011 |
| | (0.073) | (0.074) | (0.067) | (0.069) | (0.069) | (0.064) |
| PCK written test (std) | 0.279** | 0.260** | 0.204** | 0.182** | 0.186** | 0.150** |
| | (0.056) | (0.056) | (0.052) | (0.052) | (0.053) | (0.050) |
| Interview (std) | 0.316** | 0.298** | 0.270** | 0.271** | 0.283** | 0.257** |
| | (0.051) | (0.055) | (0.051) | (0.048) | (0.051) | (0.049) |
| Audition (std) | 0.174** | 0.149* | 0.152* | 0.118* | 0.104 | 0.107+ |
| | (0.062) | (0.066) | (0.064) | (0.059) | (0.065) | (0.062) |
| Recommended-pool by year FE | | √ | √ | | √ | √ |
| School FE | | | √ | | | √ |
| Adjusted R-squared | | | | 0.176 | 0.176 | 0.358 |
| F-statistic recommended-pool by year FE | | | | | 0.681 | 0.980 |
| p-value | | | | | 0.665 | 0.438 |
| F-statistic school FE | | | | | | 8.932 |
| p-value | | | | | | 0.000 |

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 1-3 each group of coefficients separated by a solid line are estimates from a separate regression. Columns 4-6 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. The recommended-pool by year FE include four mutually exclusive indicators: (i) applicants who reach the recommended pool in 2013, (ii) applicants who reach the recommended pool in 2012, (iii) applicants who pass the audition in 2011, and (iv) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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 8--Robustness to Parametric Selection Correction

| | Table 7 Columns 4 & 5 | | With control function | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years prior experience | | | | |
| 1 to 2 | 0.100 | 0.098 | 0.067 | 0.066 |
| | (0.082) | (0.083) | (0.084) | (0.084) |
| 3 to 5 | 0.163+ | 0.156+ | 0.141 | 0.131 |
| | (0.088) | (0.088) | (0.088) | (0.088) |
| 6 to 10 | 0.069 | 0.064 | 0.023 | 0.009 |
| | (0.086) | (0.087) | (0.088) | (0.088) |
| 11 or more | -0.104 | -0.109 | -0.144 | -0.155 |
| | (0.109) | (0.109) | (0.110) | (0.109) |
| Undergrad GPA (std) | 0.181** | 0.185** | 0.185** | 0.191** |
| | (0.034) | (0.035) | (0.034) | (0.034) |
| SAT math+verbal (std) | 0.019 | 0.019 | 0.034 | 0.040 |
| | (0.038) | (0.038) | (0.039) | (0.039) |
| Barron's Rank (linear 0-5) | 0.108** | 0.109** | 0.106** | 0.109** |
| | (0.027) | (0.027) | (0.027) | (0.027) |
| Master's degree or higher | 0.116+ | 0.112+ | 0.134* | 0.134* |
| | (0.062) | (0.062) | (0.063) | (0.062) |
| Location of undergrad or grad school | | | | |
| DC | -0.016 | -0.020 | -0.059 | -0.069 |
| | (0.085) | (0.087) | (0.088) | (0.087) |
| Maryland or Virginia | -0.076 | -0.075 | -0.098 | -0.096 |
| | (0.069) | (0.069) | (0.069) | (0.069) |
| PCK written test (std) | 0.182** | 0.186** | 0.167** | 0.175** |
| | (0.052) | (0.053) | (0.053) | (0.051) |
| Interview (std) | 0.271** | 0.283** | 0.237** | 0.232** |
| | (0.048) | (0.051) | (0.054) | (0.053) |
| Audition (std) | 0.118* | 0.104 | 0.084 | 0.068 |
| | (0.059) | (0.065) | (0.066) | (0.059) |
| Predicted probability of hire | | | 1.411* | -0.017 |
| | | | (0.708) | (0.681) |
| Predicted probability of hire ^ 2 | | | -1.154 | 0.865 |
| | | | (0.781) | (0.807) |
| Recommended-pool by year FE | | √ | | |
| First-stage excluded instruments Chi-2 | | | 93.46 | 11.49 |

Note: Estimates from least squares regressions with 1,581 teacher-by-year observations, and 917 unique teachers. The dependent variable is our standardized job performance factor from IMPACT evaluation component scores. Columns 1 and 2 simply repeat the estimates in Table 7 Columns 4 and 5 for convenient comparison. Columns 3 and 4 are estimated just as Column 1 is, except that we add a quadratic function of the predicted probability of hire. The predicted probability of hire is estimated using the specification reported in Table 5 Column 3 (all characteristic and score regressors and subject-applied by year fixed effects, but no recommended-pool by year fixed effects) but with additional instruments added as regressors. The hiring prediction regressions include 7,442 observations.

For the estimates reported above in Column 3, the instruments in the hire equation are four indicator variables: (i) Applicants in any year who scored above the stage 4 cut-score designated by DCPS as the treshold for the recommended pool. (ii) Applicants in 2011 who scored above the stage 3 cut-score; we assume these applicants were also placed in the recommended pool as discussed in the text. (iii) Applicants in 2011 who scored below the stage 2 cut-score but were nevertheless randomly selected to move on to stage 3. (iv) Applicants in 2011 who applied in the first weeks of the recruitment season. All of these early applicants were allowed to move on to stage 3 regardless of their scores in stage 2 or 1.

For the estimates in Column 4, the added instruments include five indicator variables: (i)-(iii) Applicants in any year who scored above the cut-score in stage 2, 3, and 4 respectively. And again for 2011 (iv) applicants randomly selected to advance or (v) early applicants automatically advanced. We also allow the slope on each stage score to be different above and below the stage cut-score, and include fixed effects for the highest stage an applicant was invited to complete. All these added coefficients are allowed to vary by year.

Clustered (teacher) standard errors in parentheses.

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

Table 9--Additional characteristics from 2011 applicants and teacher job performance

| | (1) | (2) |
|---|---|---|
| Positive spin factor (std) | 0.032 | 0.015 |
| | (0.061) | (0.062) |
| Negative spin factor (std) | -0.000 | 0.023 |
| | (0.074) | (0.074) |
| Big Five Index: Extroversion (std) | -0.001 | -0.016 |
| | (0.059) | (0.059) |
| Haberman total score (std) | 0.291** | 0.270** |
| | (0.054) | (0.054) |
| General teaching essay (std) | 0.222** | 0.187** |
| | (0.070) | (0.069) |
| Recommended-pool by year FE | | √ |

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. Each group of coefficients separated by a solid line are estimates from a separate regression. Each specification includes year-by-subject-taught fixed effects, and indicators for second year in the district and third year in the district. The recommended-pool FE include two mutually exclusive indicators: (i) applicants who pass the audition in 2011, and (ii) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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--Attrition after first year

| | Leave DCPS | | Leave school | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years prior experience (novice omitted) | | | | |
| 1 to 2 | 0.011 | 0.006 | 0.005 | -0.001 |
| | (0.043) | (0.040) | (0.047) | (0.045) |
| 3 to 5 | -0.029 | 0.010 | 0.013 | 0.056 |
| | (0.041) | (0.040) | (0.046) | (0.045) |
| 6 to 10 | -0.003 | 0.010 | 0.035 | 0.051 |
| | (0.043) | (0.039) | (0.049) | (0.045) |
| 11 or more | -0.018 | -0.029 | -0.004 | -0.019 |
| | (0.049) | (0.047) | (0.056) | (0.054) |
| Undergrad GPA (std) | 0.013 | 0.030+ | -0.002 | 0.018 |
| | (0.017) | (0.016) | (0.019) | (0.019) |
| SAT math+verbal (std) | 0.030 | 0.033+ | 0.035+ | 0.041* |
| | (0.018) | (0.019) | (0.020) | (0.020) |
| Barron's Rank (linear 0-5) | 0.000 | 0.004 | -0.001 | 0.005 |
| | (0.013) | (0.012) | (0.015) | (0.014) |
| Master's degree or higher | 0.050+ | 0.058* | 0.040 | 0.048 |
| | (0.030) | (0.028) | (0.034) | (0.032) |
| Location of undergrad or grad school | | | | |
| DC | -0.148** | -0.124** | -0.205** | -0.184** |
| | (0.037) | (0.035) | (0.040) | (0.038) |
| Maryland or Virginia | -0.052 | -0.044 | -0.053 | -0.047 |
| | (0.034) | (0.032) | (0.039) | (0.037) |
| PCK written test (std) | -0.019 | -0.010 | -0.037 | -0.029 |
| | (0.020) | (0.019) | (0.024) | (0.023) |
| Interview (std) | -0.015 | 0.005 | -0.031 | -0.007 |
| | (0.021) | (0.021) | (0.025) | (0.024) |
| Audition (std) | -0.044 | -0.037 | -0.051 | -0.043 |
| | (0.030) | (0.027) | (0.032) | (0.030) |
| IMPACT rating FE | | √ | | √ |
| Adjusted R-squared | 0.024 | 0.123 | 0.026 | 0.115 |
| DCPS mean for outcome | 0.199 | 0.199 | 0.276 | 0.276 |

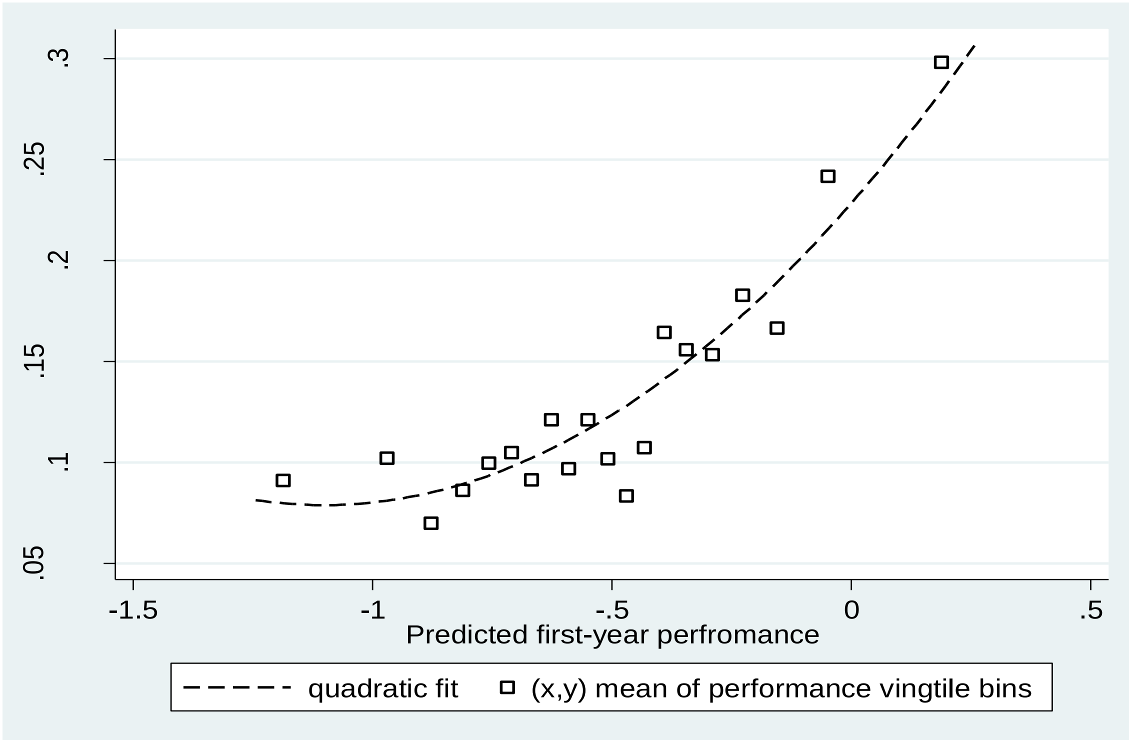
Note: Estimates from least squares regressions with 902 teacher observations. The dependent variable in Columns 1 and 2 is an indicator for having left DCPS after their first year, while in Columns 3 and 4 it is an indicator for leaving DCPS or the school in which they taught during their first year. Each specification includes year-by-subject-taught fixed effects and recommended-pool by year fixed effects. The recommended-pool by year FE include four mutually exclusive indicators: (i) applicants who reach the recommended pool in 2013, (ii) applicants who reach the recommended pool in 2012, (iii) applicants who pass the audition in 2011, and (iv) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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 11--New hire selection into schools with different characteristics

| | School free lunch percentage | |
|---|---|---|
| | (1) | (2) |
| Years prior experience | | |
| 1 to 2 | -2.768 | -2.678 |
| | (3.289) | (3.197) |
| 3 to 5 | 1.190 | 0.908 |
| | (2.939) | (2.895) |
| 6 to 10 | 4.901+ | 4.639 |
| | (2.944) | (3.068) |
| 11 or more | 4.503 | 2.659 |
| | (3.253) | (3.359) |
| Undergrad GPA (std) | -3.659** | -2.099+ |
| | (1.077) | (1.155) |
| SAT math+verbal (std) | -3.733** | -1.519 |
| | (1.315) | (1.357) |
| Barron's Rank (linear 0-5) | -3.253** | -2.003* |
| | (0.931) | (0.966) |
| Master's degree or higher | -4.593* | -4.687* |
| | (2.024) | (2.249) |
| Location of undergrad or grad school | | |
| DC | 4.003 | 4.836 |
| | (3.070) | (2.980) |
| Maryland or Virginia | 7.908** | 7.713** |
| | (2.224) | (2.299) |
| PCK written test (std) | -3.689** | -2.184 |
| | (1.414) | (1.426) |
| Interview (std) | -2.394 | -2.270 |
| | (1.653) | (1.631) |
| Audition (std) | -0.317 | -0.275 |
| | (2.045) | (1.979) |
| Recommended-pool by year FE | √ | √ |

Note: Estimates from least squares regressions with 1,557 teacher-by-year observations, and 906 unique teachers. The dependent variable is the percentage of students in the hiring school eligible for free or reduced price lunch. In column 1 each group of coefficients separated by a solid line are estimates from a separate regression. In column 2 reports 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. The recommended-pool by year FE include four mutually exclusive indicators: (i) applicants who reach the recommended pool in 2013, (ii) applicants who reach the recommended pool in 2012, (iii) applicants who pass the audition in 2011, and (iv) applicants who pass the interview but not the audition in 2011 (see the text for more details). The left out category is all other applicants. 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

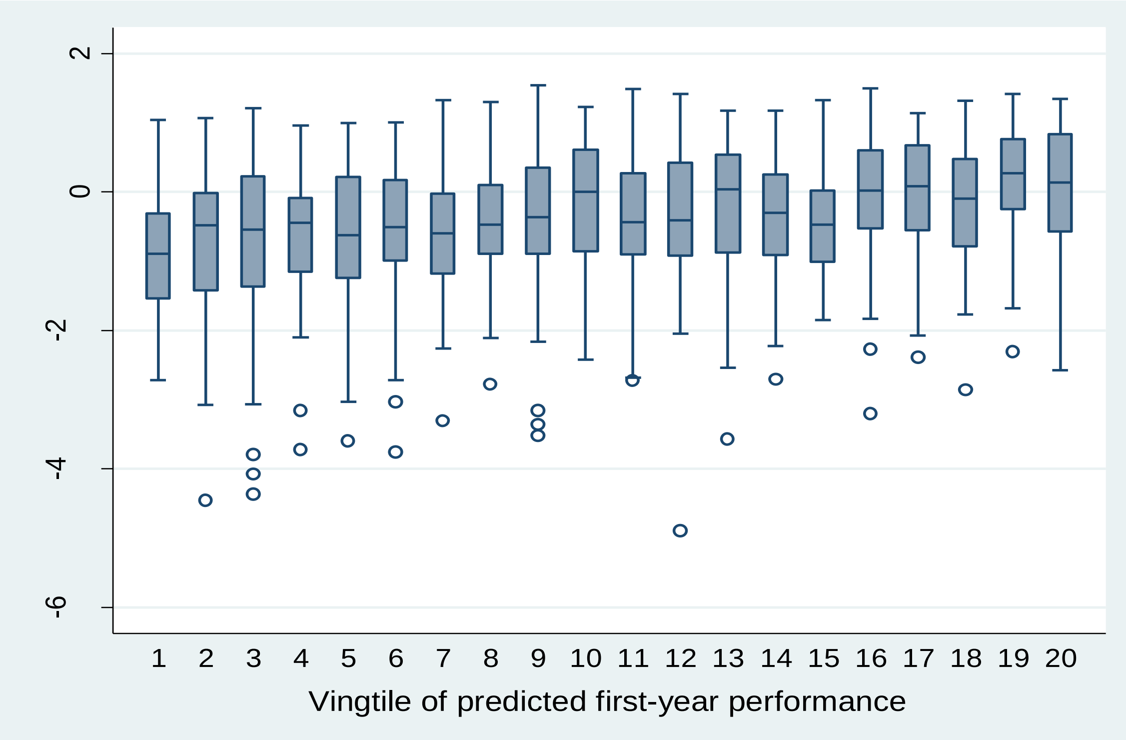
Figure 1 - Relationship between predicted performance and hiring




Note: The dashed line represents results of a regression with 7,442 observations (all applicants). In each case the binary outcome being hired by DCPS is regressed on predicted first-yer job performance, and year-by-subject-applied fixed effects. Each square marks the (x,y) mean for 20 bins. Each bin is a vingtile of predicted performance. The x-axis is limited to the 2nd through 98th percentiles of perdicted performance.

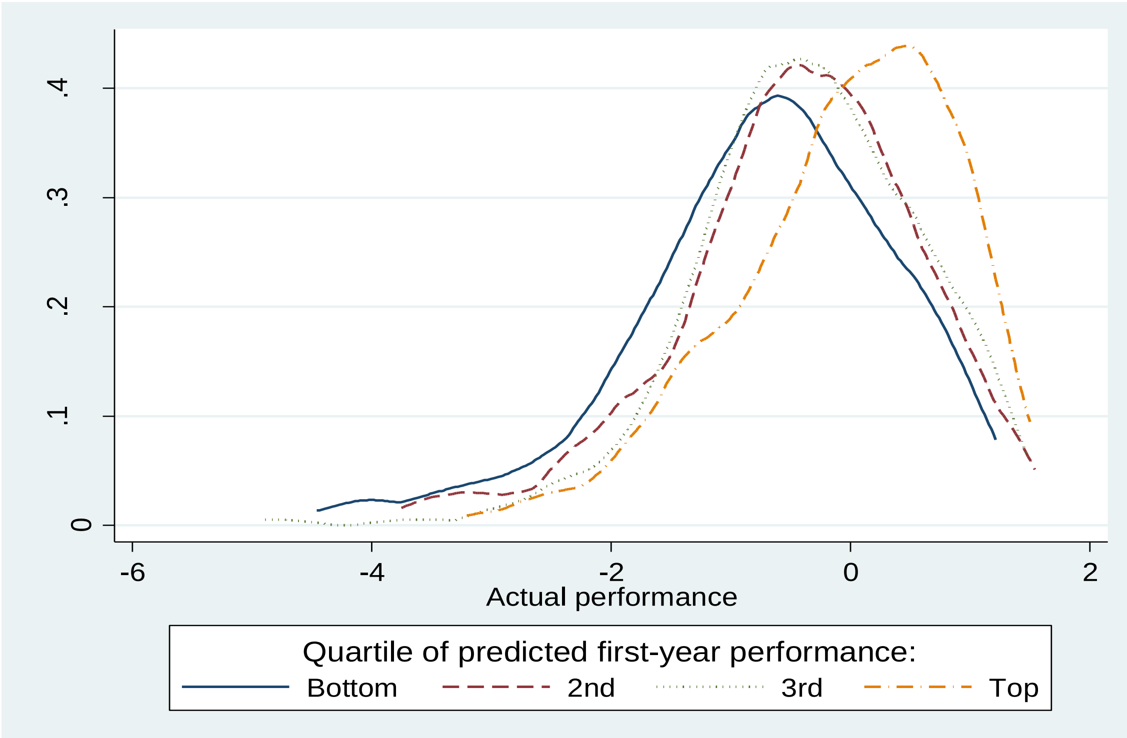
Predicted performance is estimated as follows: First, using the sample of new hires in their first year at DCPS, fit a regression similar to Tables 7 Column 4. The depednent variable is the first predicted factor from a factor analysis of IMPACT evaluation component scores from a teacher's first year at DCPS. The covariates include all of the background characteristics and application scores. The specification also includes subject-taught by year fixed effects. Second, the estimated coefficients from that regression are applied to the applicants sample. This predicted performance measure does not include differences between the subject-taught by year fixed effect groups.

Figure 2 - Relationship between predicted performance and actual performance



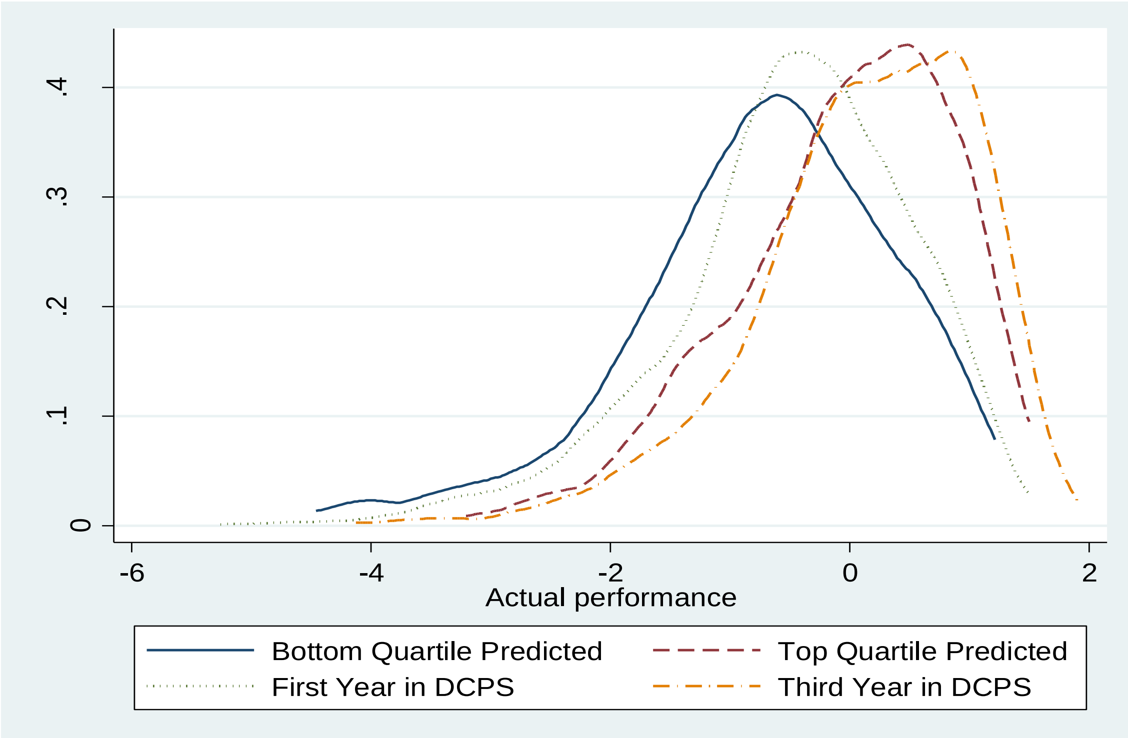

Note: Box-plots of actual performance for each vingtile of predicted performance. Actual performance is the first predicted factor from a factor analysis of IMPACT evaluation component scores. Predicted performance is the fitted value obtained after the following regression: Using the sample of new hires, fit a regression similar to Table 7 Column 4. The depednent variable is the first predicted factor of IMPACT scores. The covariates include all of the background characteristics and application scores. The specification also includes subject-taught by year fixed effects.

Figure 3 - Relationship between screening measures and performance




Note: Kernel densities estimated separately by quartile of predicted performance using teacher-by-year observations. Predicted performance is the fitted value obtained after the following regression: Using the sample of new hires, fit a regression similar to Table 7 Column 4. The depednent variable is the first predicted factor of IMPACT scores. The covariates include all of the background characteristics and application scores. The specification also includes subject-taught by year fixed effects.

Figure 4 - Relationship between screening measures and performance, compared to experience




Note: Kernel densities estimated separately for the top and bottom quartile of predicted performance using teacher-by-year observations. Predicted performance is the fitted value obtained after the following regression: Using the sample of new hires, fit a regression similar to Table 7 Column 4. The dependent variable is the first predicted factor of IMPACT scores. The covariates include all of the background characteristics and application scores. The specification also includes subject-taught by year fixed effects. Also kernel densities estimated separately for teachers in their first year working in DCPS and teachers in their third year working in DCPS.